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Application of Physiological Self-Regulation and Adaptive Task Allocation Techniques for Controlling Operator Hazardous States of Awareness

Lawrence J. Prinzel, III and Alan T. Pope
Langley Research Center, Hampton, Virginia

Frederick G. Freeman
Old Dominion University, Norfolk, Virginia

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National Aeronautics and
Space Administration

Langley Research Center
Hampton, Virginia 23681-2199

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ABSTRACT

Prinzel, Hadley, Freeman, & Mikulka (1997) found that adaptive task allocation significantly enhanced performance only when used at the endpoints of the task workload continuum (i.e., very low or high workload), but that the technique degraded performance if invoked during other levels of task demand. These researchers suggested that other techniques should be used in conjunction with adaptive automation to help minimize the onset of hazardous states of awareness (HSA) and keep the operator "in-the-loop." The paper reports on such a technique that uses psychophysiological self-regulation to modulate the level of task engagement. Eighteen participants were assigned to three groups (self-regulation, false feedback, and control) and performed a compensatory tracking task that was cycled between three levels of task difficulty on the basis of the electroencephalogram (EEG) record. Those participants who had received self-regulation training performed significantly better and reported lower NASA-TLX scores than participants in the false feedback and control groups. Furthermore, the false feedback and control groups had significantly more task allocations resulting in return-to-manual performance decrements and higher EEG difference scores. Theoretical and practical implications of these results for adaptive automation are discussed.

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INTRODUCTION

Human error remains the largest single cause of accidents in aviation. The FAA has reported that human error accounts for 66% of air carrier incidents and accidents, 88% of general aviation and 79% of commuter accidents (FAA, 1990). Therefore, it is not surprising that human factors have received much attention in recent years. The Aviation Safety Research Act of 1988, for example, directed the FAA to increase research to improve the human factors involved with aviation safety. Unfortunately, solutions to human error have focused on automation of tasks that have led increasingly to the pilot as backup or supervisory controller of automation.

The term, "pilot error" can be misleading since it implies that the pilot alone was the sole cause of the incident or accident that occurred. However, there has been increasingly a realization of the importance of other factors (e.g., organizational accidents; Maurino, Reason, Johnston, & Lee, 1995) that have as much, if not more, of a role in contributing to their onset. Schutte et al. (1999) noted that the pilot is actually the last "line of defense" or "error filter" and is an important element in preventing accidents. Although pilot error is often assigned as the most cited cause of accidents, it is unknown as to how many accidents were prevented by having the pilot present in the cockpit. Certainly, pilots have prevented many accidents. Alarmingly, the increase in automation from a technology-centered (Billings, 1997) perspective has actually increased the possibility of human error. Pilots are expected to remain alert even during often boring periods and skillfully assume control in the event of system failure. In addition, the complacency that may accompany prolonged reliance on automation may impair a pilot's ability to "return-to-manual" control from the "electronic team members" (a.k.a. Automation).

The benefits of automation have been well-documented and include increased fuel economy, reduction of manual workload and fatigue, economy of cockpit space, increased precision of flight maneuvers and navigation to name but a few. However, the benefits realized with increased automation have not been without cost. Research has shown that automation also has a number of problems associated with its use. These problems have included monitoring inefficiency, loss of situation awareness, increased mental workload, cognitive overhead, poor return-to-manual control, decreased vigilance and inattention, mode unawareness, and complacency.

Schutte and Willshire (1997) noted that the "technology-centered" flight deck is responsible for many of the flight crew errors witnessed as a result of increased use of automation (see also Billings, 1997). The concern centers around the *can* versus the *should* of flight deck design. Current flight deck designs often take into account physical limitations, such as visibility and legibility requirements, but many neglect the cognitive limitations of pilots. Questions usually asked are, *Can a pilot operate this?* instead of *Is this the way the pilot should operate this?*

Such a concern has resulted in a number of "human-centered" automation concepts that have been proposed to improve the pilot-automation interaction. One such concept has been termed adaptive task allocation or adaptive automation. Adaptive automation refers to automation that is invoked in response to changing task demands (Morrison & Gluckman, 1994). Unlike traditional forms of automation, adaptive automation attempts to regulate pilot situational awareness and other capabilities through real-time task allocation between the automated system and pilot (Rouse, 1977; Scerbo, 1996).

Adaptive automation is still in a conceptual phase and a number of research issues still need to be addressed before widespread acceptance will be possible. Woods (1996), for example, noted that automation represents "apparent simplicity, real complexity" referring to the idea that automation transforms the nature of pilot-automation interaction. New forms of automation may bring with them new problems. Adaptive automation may not be an exception to such an observation. Rudisill (1994) found that pilots tended to be positive about technological innovations, but still had concerns about advanced forms of automation. They noted that advanced automation kept them "out-of-the-loop" and that pilots constantly needed to monitor what the automation was doing. Also, advanced automation tended to increase their workload and decrease cockpit management and flight crew communication.

Pilots reported that what they wanted were new approaches to training that would ameliorate some of these problems associated with advanced automation.

The aviation community has adopted a number of training techniques to facilitate effective pilot-automation interaction in the cockpit. Concepts, such as crew resource management (Seamster, Boehm-Davis, Holt, & Shultz, 1998; Wiener, Kanki, & Helmreich, 1993), have been endorsed by the Federal Aviation Administration (FAA) and the airlines to help improve team interaction and performance. However, the attention directed toward the *inter-* personal issues has been largely at the expense of *intra*-personal factors that also warrant consideration (Simmon, 1998). The airlines have initiated training programs that contain training in areas such as decision-making, workload, etc., but they usually are not given as much weight as that of the inter-personal aspects of human factors. There have been several recent accidents which suggest that a more balanced approach may be necessary. For example, the accident at Cali, Columbia on December 20, 1995 showed the need for training in crew resource management. However, inter-personal errors were not the only ones committed. Simmon's (1998) review of the accident also indicated a deficiency of individual, intra-personal cognitive skills including complacency, cognitive biases, fixations, inattention, reasoning and problem-solving mistakes. Simmon noted that, "...most pilots develop satisfactory intrapersonal skills without training. Nevertheless, specific intrapersonal training should be developed and presented to all pilots to increase awareness of human error and the counteracting strategies that can reduce human error." He suggested that human factors training programs should include training to understand and recognize hazardous thought patterns and hazardous states of awareness and also how best to self-manage them; termed "cognitive resource management."

The present paper reports on such a training method that may complement the use of adaptive automation that focuses on intra-personal, self-regulation of hazardous states of awareness. The research to examine the method was based on results reported by Prinzel, Hadley, Freeman, & Mikulka (1999) who cycled a compensatory tracking task between manual and automatic task modes in response to six task engagement levels indexed with electroencephalographic (EEG) measures. They found that short-cycle adaptive task allocation improved performance, subjective reports of workload, and increased engagement as reflected by event-related potentials (ERP). The ERP is a characteristic waveform derived from the EEG that is time-locked to specific events; components of the waveform correspond to different stages of information processing and have been found to be sensitive measures of mental workload (Parasuraman, 1990; Wickens, Isreal, & Donchin, 1977; Wickens, Kramer, Vanasse, & Donchin, 1983). However, these authors also found that there were increased return-to-manual deficits in which task performance suffered significantly just after a task allocation. Additionally, the N1 and P3 component of the ERP showed a significant decrease in amplitude and increase in latency after a task allocation also indicating an increase in workload. A finer grain analysis further revealed that these results were confined to the task allocations that occurred in response to the middle range of the subject's engagement levels. Therefore, adaptive task allocation may be best reserved at the endpoints of the task engagement continuum and other techniques should be used in conjunction with adaptive automation to help minimize the onset of hazardous states of awareness (Pope & Bogart, 1992) and keep the pilot "in-the-loop." One training technique that may be employed is psychophysiological self-regulation.

Psychophysiological self-regulation refers to the ability of a person to control affective and cognitive states based on autonomic (ANS) and central nervous system (CNS) functioning. The techniques use physiological markers of these states and provide biofeedback so that the person learns these associations and how to modulate their occurrence. A biofeedback system is actually an example of a closed-loop feedback system. While engineering feedback control systems regulate physical variables, biofeedback systems take advantage of the benefits of knowledge-of-results and immediate reinforcement effects to facilitate learning of voluntary physiological control. Such systems can be used to reveal information about relationships among physiological and psychological variables, as proposed by Mulholland (1977). Knowledge of these relationships can, in turn, be used to assess the interaction of human operators with complex systems.

Currently, there has not been much research conducted on the use of physiological self-regulation for performance enhancement (see Norris & Currieri, 1999 for review). With regards to aviation, there has been virtually no research examining the efficacy of self-regulation for improving pilot performance. One of the few studies that have been conducted was reported by Kellar et al. (1993). They found that self-regulation training, termed "Autogenic-Feedback Training (AFT)", may be an effective countermeasure to stress-related performance decrements. Additionally, these authors reported that AFT improved crew coordination and communication and, therefore, may serve as a valuable adjunct to CRM training.

Although Kellar et al.'s (1993) research demonstrated the value of physiological self-regulation for controlling stress-related responses to emergency conditions, stress represents only one of the hazardous states of awareness that pilots may encounter during flight. Other states include boredom, inattention, complacency, fatigue, etc. that may play an equal or greater role in contributing to incidents and accidents in aviation.

Research conducted at the Crew Hazards and Error Management laboratory at NASA Langley Research Center and the Psychology Department at Old Dominion University has been directed towards the development of a biocybernetic, closed-loop system that uses psychophysiological measures to help control the onset of "hazardous states of awareness." The system was developed in response to considerable evidence that, as the modern cockpit became more automated, pilots spent less time actively controlling such systems and more time passively monitoring system functioning. This type of task demand challenges human capabilities for maintaining sustained attention and engagement in the operation. Mental engagement under such automated conditions may not be sufficient to promote an effective state of awareness. The term "hazardous state of awareness" was coined to refer to phenomenological experiences such as daydreaming, "spacing out" from boredom, or "tunneling" of attention, reported in aviation safety incident reports (Pope and Bogart, 1992). Hazardous states of awareness such as preoccupation and excessive absorption and the associated task disengagement have been implicated in operator errors of omission and neglect with automated systems. A need has been recognized in the human factors research field for better methods to objectively identify the occurrence of these states in human operators and to specify the system design factors that affect these states.

This closed-loop method was developed to support the determination of optimal human (manual)/system (automated) task allocation "mixes," based upon a brain activity criterion for positive mental engagement. In this method, an experimental subject interacts with a set of tasks presented on a desktop computer display while the subject's electrical brain activity is monitored. The level of automation of the tasks may be varied so that all, none, or a subset of tasks require subject intervention, enabling a range of levels of demand for operator involvement in system management to be imposed. A biocybernetic loop is formed by adjusting the number of manual tasks imposed on the subject, based on electroencephalographic (EEG) signals reflecting an operator's engagement in the task set. An optimal number of manual versus automated tasks is arrived at by allowing the closed-loop (negative) feedback system to attain stable operation, reflecting stable engagement, and is defined by the subset of tasks that maintain stable operation.

Candidate indices, in the closed-loop method, are judged on the basis of their relative strength in producing expected feedback control system phenomena (stable operation under negative feedback and unstable operation under positive feedback) (Muholland, 1977). Pope, Bogart, & Bartolome (1995) first reported that the EEG band ratio of beta / (alpha + theta) best discriminated between states of engagement. The "engagement index" was derived from recent research in vigilance and attention (Lubar, 1991; Streitberg et al., 1987). For example, Siervaag (1993) et al. observed decreases in theta with increases in task difficulty. Increases in workload and arousal have also been shown to be correlated with increases in beta activity (Davidson, 1988) and decreases in alpha activity (Ray & Cole, 1985). Lubar and his associates have further argued that low levels of attention are associated with increased theta power and concomitant decreased beta power. Their research, and the research of others (e.g., Consistency Index; Cox et al., 1999), have employed the use of EEG engagement ratios for biofeedback assessment of ADHD patients. Therefore, the closed-loop system may also function as a training protocol in that the subject is rewarded for producing an EEG pattern that causes the automated system to share more of the work. With practice, a subject may learn how to deliberately control subtask allocation to the level at which he or she prefers to work.

Research has shown promise for the closed-loop system to serve in both regulatory and developmental roles for the use of psychophysiology in adaptive automated systems (Byrne & Parasuraman, 1996). To date, however, our research had focused on the examination of system parameters for the real-time task allocation of automation modes (i.e., manual; automatic). Furthermore, the task mode alone was responsible for determining task allocation sequencing; that is, what automation mode the task was in determined the engagement level of the participants which therein determined subsequent task modes. However, research in biofeedback and self-regulation has demonstrated the capabilities that people have to control their own engagement states. Therefore, considering the theoretical foundation that the system is based upon, it seems reasonable to explore the biofeedback potential of the system as a training tool for developing self-regulation skills for managing hazardous states of awareness.

To examine the efficacy of physiological self-regulation, participants were assigned to three experimental groups (self-regulation; false feedback; control). The self-regulation group was provided neurofeedback training that focused on learning the patterns of hazardous states of awareness and performance knowledge-of-results (KR). To guard against the chance that just providing feedback may be responsible for producing positive effects, the false feedback group was given random feedback regarding their mental engagement state and performance. The control group was provided no feedback. It was hypothesized that physiological self-regulation training would provide tools for participants to manage their cognitive resources by self-regulation of their engagement states. The expected outcomes of which would be better performance, lower reported subjective workload, and fewer automation task allocations for these participants compared to those in the false feedback and control groups.

METHOD

Participants. Eighteen Old Dominion University students served as participants for the study. Students were given experimental credit or paid $20 for their participation. Participants were randomly assigned to either the self-regulation (6 participants), false feedback (6 participants) or control (6 participants) condition.

Experimental Task**.** The task used for the experiment was a compensatory tracking task from the Multi-Attribute Task Battery (Comstock & Arnegard, 1992). The Resource Management and Monitoring tasks were automated with the exception of a single automation failure 22 minutes into the final experimental session. The task requires participants to use a joystick to maintain a moving circle, approximately 1 cm in diameter, centered on a .5 cm by .5 cm cross located in the center of the screen. Failure to control the circle results in its drifting away from the center cross. The tracking task was a 4:3 horizontal-to-vertical sine wave driving function. There were two manual tracking conditions used: low and high tracking difficulty with the difference between the two being the time it took to step through the driving function (1:3 time ratio, respectively). Arnegard (1992) reported that there was a significant difference in performance and reported workload between these two tracking conditions. Also, there was an automatic tracking condition in which the system was responsible for performing the task.

Experimental Variables. Tracking performance was measured by root-mean-squared-error (RMSE), and subjective workload was assessed using the NASA-TLX (Hart & Staveland, 1988). Relative power of theta, beta, and alpha at each cortical site was measured. The EEG engagement index (see below) used was 20 beta / (alpha + theta) and has been shown to be a valid index of task engagement (Freeman, Mikulka, Prinzel, & Scerbo, 1999; Freeman, Mikulka, Scerbo, Prinzel, & Clouatre, in press; Prinzel, Freeman, Scerbo, Mikulka, & Pope, in press; Pope, Bogart, & Bartolome, 1995). Other dependent variables included the number of task allocations between engagement levels and return-to-manual deficits measured by each 30-second period of tracking RMSE after each task allocation.

EEG Recording and Analysis. The EEG was recorded from sites Cz, Pz, P3, and P4. A ground site was used located midway between Fpz and Fz. Each site was referenced to the right mastoid. The total EEG power from the bands of theta, alpha, and beta for each of the three sites was measured. The EEG frequency bands were set as follows: alpha (8-13 Hz), beta (13-22 Hz), and theta (4-8 Hz).

EEG Engagement Index. Prior to starting the task, a five-minute EEG baseline period was recorded. The mean of the EEG engagement index derived from the baseline EEG was then fed into the biocybernetic system. The system used a moving window process in which a derived EEG index was calculated over a 40-second window. The window was advanced two seconds and a new average was derived. This moving window process continued for the duration of the trial. An increasing EEG index indicated that the participant's arousal level was increasing and a decreasing index indicated that arousal was decreasing.

There are six levels by which the system determines task allocation. Levels 1-3 reflect decreasing engagement and levels 4-6 reflect increasing engagement relative to baseline measures. Within these two categories, levels are determined based upon how variable the EEG engagement index was during baseline performance. The algorithm used to determine the level of the task the participant would be placed is as follows: A level 3 allocation would be assigned if the index was between 0 and –0.5 standard deviations (SD) below the baseline mean; level 2 would be assigned for an index between –0.5 to –1.00; level 1 would be assigned if the index was below –1.00. For indexes above the baseline mean, level 4 would be assigned if the index was between 0 and +0.5 SD above the mean; level 5 between +0.5 and +1.00; and level 6 above +1.00.

All participants were instructed that the system measured six different engagement levels, and that a high difficulty, manual task allocation would occur if the engagement level went to Level 1 (low task engagement) or automatic task allocation if it went to Level 6 (high task engagement). When the engagement level was between Levels 2 and 5, the tracking task was in the manual, low difficulty task mode. If the index indicated that the participant's arousal level was 1 SD above baseline (level 6), the task was switched from the manual task condition to the automatic task condition. If the index indicated that arousal was 1 SD below baseline (level 1), the task was switched from either the automatic or low difficulty, manual task condition to the high difficulty, manual task condition.

Experimental Groups. There were three separate experimental groups for this study (self-regulation, false feedback, control). Participants in the self-regulation group were provided biofeedback regarding their task engagement level while they participated in two 30-minute training sessions. During the first training session, feedback on engagement level was provided in the right-hand corner of the tracking window (e.g., "Level One") during the training sessions, and they were encouraged to try and maintain Level 3 or 4 engagement levels. Furthermore, these participants were provided knowledge-of-results (KR) feedback on their performance as to their performance (root-mean-squared-error; RMSE) during the experimental session. The feedback was provided in the lower left-hand box of the tracking window. During the second training session, participants were cued by a computer-generated tone to estimate what their engagement level was at particular times during the session (i.e., pressing F1-F6 keys that corresponded to engagement levels 1-6). Feedback was then provided as to how close their estimation was to their actual engagement level. All participants in the self-regulation condition achieved a 70% level of correct identifications.

The false feedback group was presented with identical training protocols as in the self-regulation condition. The only exception was that these participants were provided incorrect feedback as to their task engagement level and performance. False feedback was given as +/- 1 engagement level and +/- 5 RMSE from actual task engagement and performance levels. These values were determined during pilot testing in which participants commented that these incorrect values seemed realistic to their current state and performance (i.e., the false feedback provided enough diagnosticity as to be believable). Participants in the control condition were not provided with any feedback concerning their task engagement and performance, but these participants did complete two 30-minute "no training" sessions.

Experimental Procedure. Before each task run began, the participant's scalp was prepared with rubbing alcohol and electrolyte gel. A reference electrode was then attached to their right mastoid by means of electrode tape. ECI Electro-Gel conductive gel was then placed in the reference electrode with a blunt-tip hypodermic needle. Electrode gel was also placed into each of the four electrode sites (Cz, Pz, P3, P4), the reference, and the ground site. Using the blunt-tip hypodermic needle, the scalp was then slightly abraded to bring the impedance level of the sites, relative to the ground, to less than 5 KOhms.

All participants performed two 90-minute training sessions and were thoroughly briefed as to how the system worked and what task engagement levels meant, etc. Participants were invited back one week later to participate in the assessment session. The time frame was chosen to check the robustness of the training effect.

During the assessment sessions, participants in all three groups were allowed to practice the tracking task for five minutes, or until they had reached asymptotic performance level for the task. Research (Arnegard, 1992) with the tracking task has demonstrated that it does not require much training and participants can perform the task within a few minutes. There were no differences found between the three groups during the 5-minute practice ($\underline{p} > .05$). All participants then performed one 30-minute assessment trial, and no neurofeedback was provided to either group. The NASA-TLX and a post-assessment interview were completed once the session had ended.

RESULTS

Tracking Performance. A main effect was found for tracking performance, $F(2,15) = 82.86$, $\underline{p} < .0001$. Participants in the self-regulation group performed significantly better ($\underline{M} = 2.03$ $\underline{SD} = 0.28$) than participants in either the false feedback group ($\underline{M} = 7.77$ $\underline{SD} = 0.90$) or control group ($\underline{M} = 6.62$ $\underline{SD} = 0.87$). Furthermore, return-to-manual deficits were found to be higher for participants in the control condition ($\underline{M} = 15.43$ $\underline{SD} = 3.98$) and false feedback condition ($\underline{M} = 16.89$ $\underline{SD} = 4.21$) than participants in the self-regulation condition ($\underline{M} = 9.87$ $\underline{SD} = 2.56$), $F(2,15) = 10.45$, $\underline{p} < .05$. Figure 1 represents tracking RMSE across each 10-minute experimental block.

Electroencephalogram. An EEG difference score was calculated by subtracting the mean for each participant's task EEG Engagement Index from the mean of his or her baseline EEG engagement index (EEG Index $_{task}$ – EEG Index $_{baseline}$). The EEG difference score was found to be significantly smaller in the self-regulation condition ($\underline{M} = 2.73$ $\underline{SD} = 2.19$) than in either the false feedback ($\underline{M} = 14.36$ $\underline{SD} = 6.61$) or control ($\underline{M} = 12.86$ $\underline{SD} = 8.24$) conditions, $F(2, 15) = 6.18$, $\underline{p} < .01$. EEG engagement index values for each condition were: Self-regulation ($\underline{M} = 17.00$ $\underline{SD} = 6.08$), false feedback ($\underline{M} = 24.60$ $\underline{SD} = 3.28$), and control ($\underline{M} = 28.94$ $\underline{SD} = 12.10$). No significant differences were found between the three groups' baseline EEG engagement index ($\underline{p} > .05$). Figure 2 shows the EEG difference score across each 10-minute experimental block.

Subjective Workload. An ANOVA revealed that participants in the self-regulation group ($\underline{M} = 38.00$ $\underline{SD} = 12.08$) rated workload to be significantly lower than participants in either the false feedback ($\underline{M} = 58.66$ $\underline{SD} = 16.46$) or control groups ($\underline{M} = 66.66$ $\underline{SD} = 17.28$), $F(2,15) = 5.50$, $\underline{p} < .05$.

Task Allocations. An ANOVA was performed on the number of task allocations made between automation levels. The analysis was done because the intention of self-regulation training is to reduce the need to make task allocations in order to keep the operator "in-the-loop." A main effect was found between conditions for number of total task allocations, $F(2,15) = 7.52$, $\underline{p} < .01$. There were significantly fewer task allocations made in the self-regulation condition ($\underline{M} = 19.00$ $\underline{SD} = 7.79$) than in either the false feedback ($\underline{M} = 40.50$ $\underline{SD} = 12.09$) or control conditions ($\underline{M} = 40.33$ $\underline{SD} = 12.59$). An examination of Figure 3 shows that most of the task allocations made in the self-regulation condition were confined to Levels 3 and 4 which was considered optimal for task engagement and performance. Task allocations in the other two conditions were spread roughly equally across the automation levels.

Although participants in the false feedback and control groups had more task allocations to the automated and difficult, manual task conditions, these participants spent only approximately 10% and 12% of their time in either of these two task conditions (automated and difficult, manual, respectively). Participants in the self-regulation group, however, also spent approximately 11% and 9% of their time in the automated and difficult, manual task conditions, respectively. Therefore, the differences found in performance can not be attributed solely to different task demands since each group did perform all three task conditions for equal amounts of time.

DISCUSSION

Sarter and Woods (1994) remarked that, with the presence of multiple modes of automation, flying becomes a task of orchestrating a "suite of capabilities" for different sets of circumstances. For example, Endsley & Kiris (1994) found that higher levels of autonomy remove the operator from the task at hand and can lead to poorer performance during automation failures; a problem that may be more acute with increasing numbers of automation task mode changes. Scerbo (1996) noted that automated systems with multiple task modes are difficult to learn and may increase the workload associated because the intention of system behavior may not be transparent to the pilot resulting in "automation surprises." Because of this, traditional approaches to training no longer seem adequate to prepare pilots for their new task of supervisory control of highly dynamic, complex systems. These new forms of automation, such as adaptive automation, will require new approaches to and objectives for training.

"Human-centered" automation design details how technology changes human-automation interaction and how best to support the roles that people now have to play as supervisory controllers, exception handlers, and monitors and managers of automated resources (Billings, 1997; Palmer et al., 1994). Self-regulation may represent another tool for supporting human-centered design. Participants in the self-regulation condition were better able to maintain their task engagement level within a narrower range of task modes thereby reducing the need for task mode changes. The effect of this was an increase in task performance as well as a decrease in reported workload. Furthermore, these results may have been due to the increase in return-to-manual performance deficits witnessed in the control and false feedback conditions. The self-regulation group had fewer task mode changes, and when there was a change (i.e., from either Levels 1 or 6), these participants had significantly lower tracking error scores just after a task mode change than those participants in the false feedback or control conditions.

The neurofeedback provided during training may have allowed these participants to better manage their "cognitive resources" and thereby regulate their engagement state allowing them to better respond to a change in automation mode. The other conditions, however, were not given neurofeedback or were given false feedback and, therefore, the schedule of task mode changes may have been opaque to them. Post-experimental interviews with these participants suggested that they indeed felt unaware (e.g., did not feel that their engagement level was low when it changed to difficult manual tracking condition) as to when and why the task switched from one task mode to another. Furthermore, they reported that they didn't know how to increase their task engagement and effect a task mode change.

PRACTICAL APPLICATIONS

For adaptive automation to be successful, Scerbo (1996) described a number of issues that need be addressed. One of these issues is that there is a need to understand how this new form of technology will change the human-automation interaction and to develop training methods to help support the development of adaptive automation. The results of the present study support other research that have demonstrated that physiological self-regulation could enhance cognitive resource management skills of pilots and complement the benefits of adaptive automation. Furthermore, although adaptive automation maybe some years away before the technology becomes viable enough to be considered an option for automation design, psychophysiological self-regulation training may have current application potential outside that of adaptive automation.

Rigner and Dekker (2000) stated that current pilot training (e.g., Multi-Crew Cooperation and Crew Resource Management) is inadequate to develop the new attentional and knowledge requirements necessary to support pilot-automation interaction in the modern automated cockpit. An example of the importance of improving pilot training is the Cali, Columbia accident (December 20, 1995). The accident highlighted the importance of Crew Resource Management (CRM). However, Simmon's (1998) review of the accident noted that the majority of errors indicated a deficiency of individual, intra-personal cognitive skills including complacency, cognitive biases, fixations, inattention, and reasoning and problem-solving mistakes. Simmon noted that, "...most pilots develop satisfactory intrapersonal skills without training. Nevertheless, specific intrapersonal training should be developed and presented to all pilots to increase awareness of human error and the counteracting strategies that can reduce human error" (p.16). He suggested that human factors training programs should include training to understand and recognize hazardous thought patterns and hazardous states of awareness and also how best to self-regulate these states. Furthermore, Crew Resource Management training should include a one-day intrapersonal human factors training program that includes both human-error training and skills and strategy training. These would focus on such topics as understanding the etiology and characteristics of hazardous states of awareness, development of effective thought patterns, attention-management and memory techniques, and physiological skills to enhance mental state. Such a training approach, termed "<u>C</u>ognitive <u>R</u>esource <u>M</u>anagement", could be combined with current inter-personal "<u>C</u>rew <u>R</u>esource <u>M</u>anagement", to produce a comprehensive CRM-Squared (CRM + CRM = CRM^2) training program that could support pilots' new roles as supervisory controllers.

Research in the Physiological / Psychological Stressors and Factors (PPSF) research program at NASA Langley Research Center and Ames Research Center has been directed towards developing a CRM^2 strategy for reducing the onset of pilot hazardous states of awareness. It reflects a NASA objective of "making a safe aviation system even safer" by developing methods to dramatically reduce the effects of human error (NASA, 1998; 1999). Our work has focused on a number of areas with the goal of improving cognitive resource management, including that of physiological self-regulation reported here. Other areas include adaptive task allocation, adaptive interfaces, hazardous unawareness modeling, cognitive awareness training, and stress-counter response training. The hope is to design countermeasures and training interventions that may supplement existing strategies, such as Crew Resource Management, but which focus more on the intra-personal aspects of enhancing flight safety. Together with other NASA-led programs as well as industry and academic partners, the goal of reducing the aircraft accident rate by a factor of 5 within ten years and by a factor of 10 within twenty-five years can hopefully become a reality (NASA, 1999).

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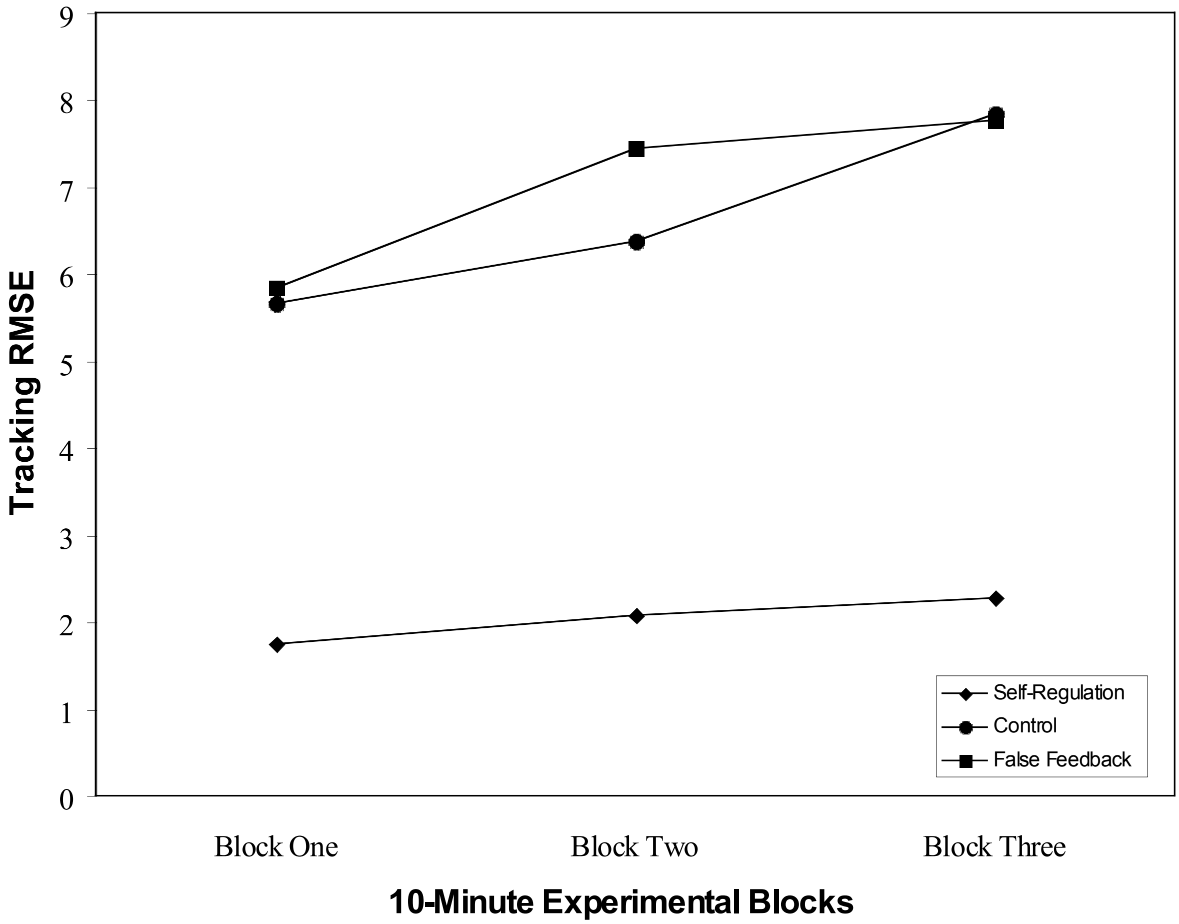

Figure 1. Tracking RMSE across 10-minute blocks.

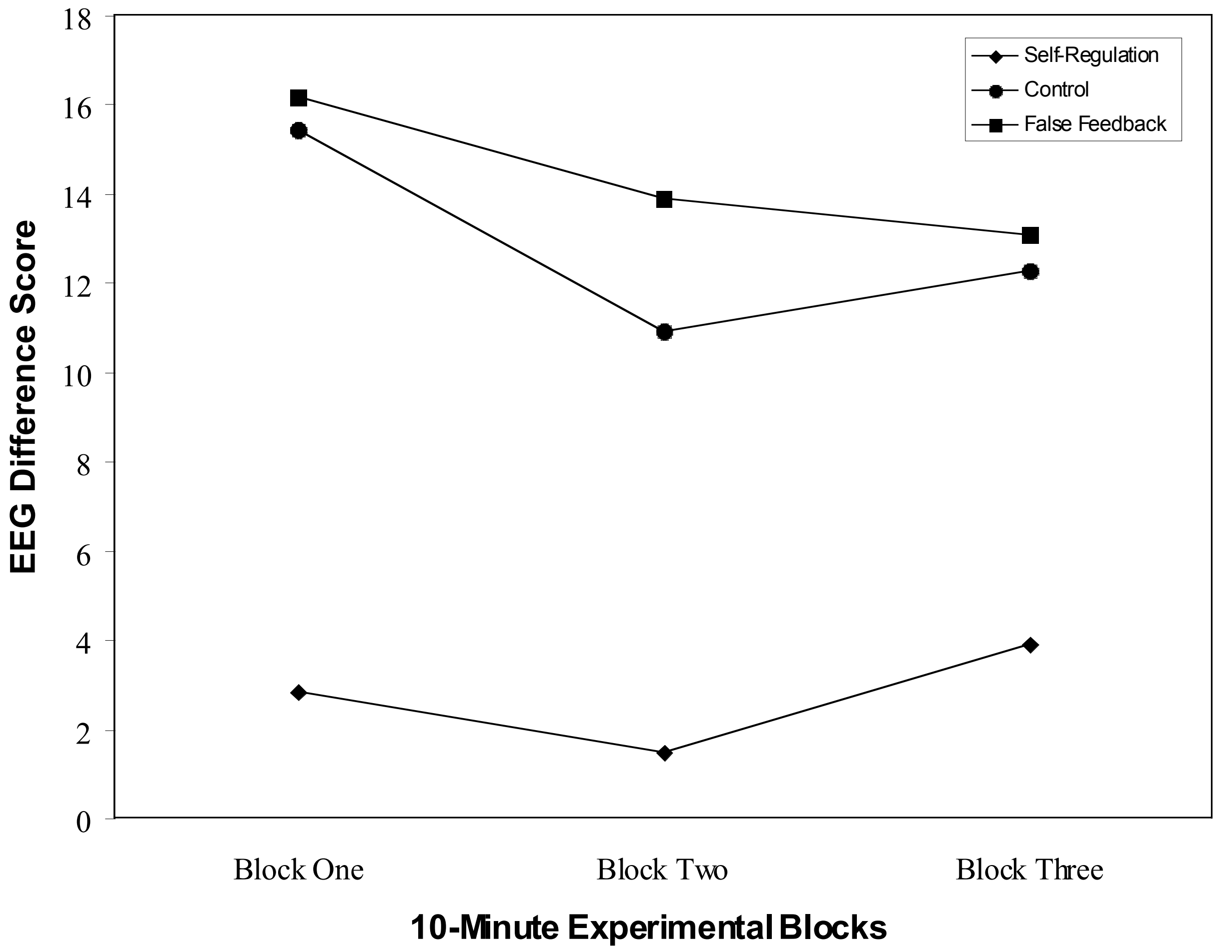

Figure 2. EEG difference score across 10-minute blocks.

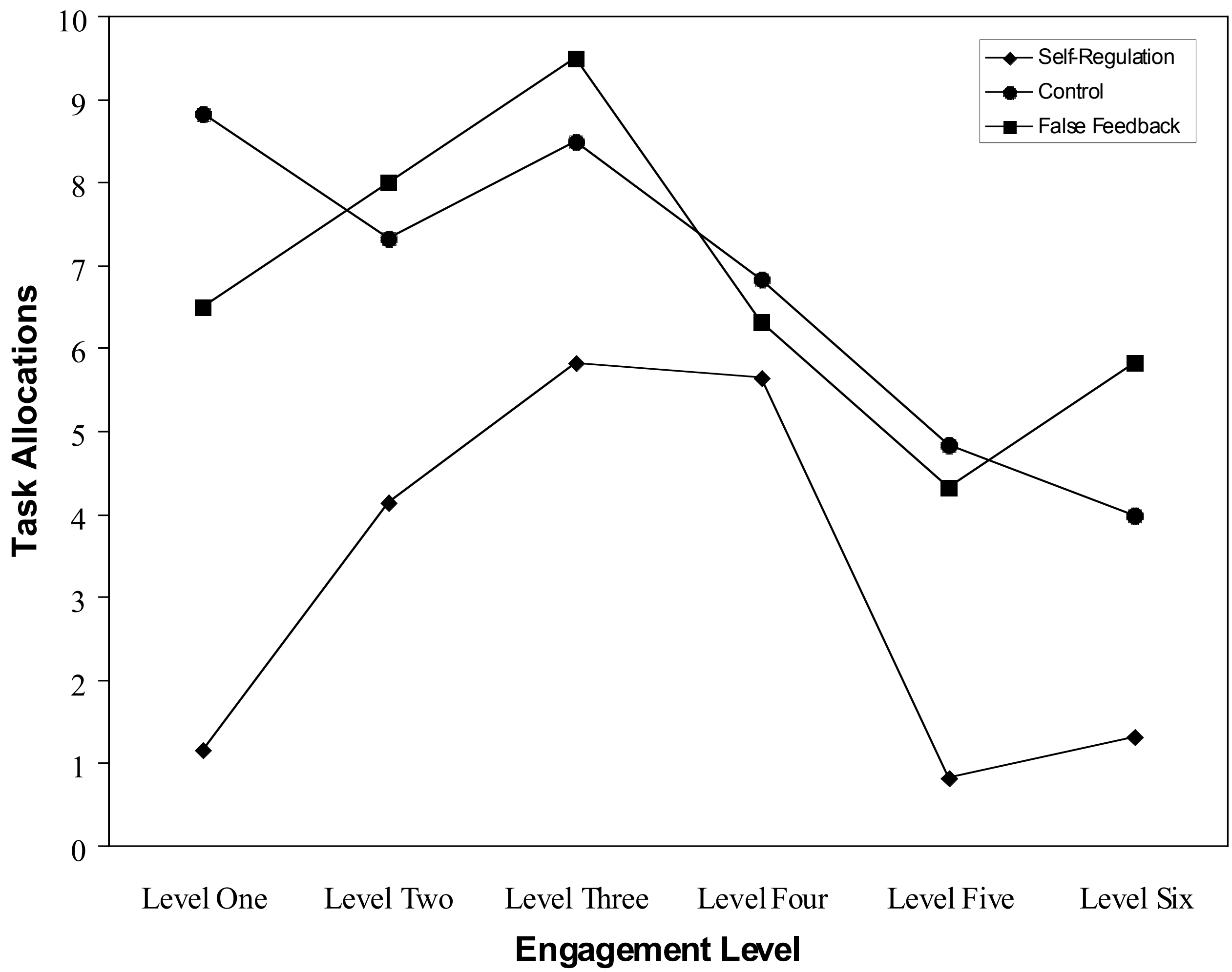

Figure 3. Task Allocations within each Engagement Level.

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Lawrence J. Prinzel, III, Alan T. Pope, and Frederick G. Freeman

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13. ABSTRACT (Maximum 200 words)
Prinzel, Hadley, Freeman, & Mikulka (1997) found that adaptive task allocation significantly enhanced performance only when used at the endpoints of the task workload continuum (i.e., very low or high workload), but that the technique degraded performance if invoked during other levels of task demand. These researchers suggested that other techniques should be used in conjunction with adaptive automation to help minimize the onset of hazardous states of awareness (HSA) and keep the operator "in-the-loop." The paper reports on such a technique that uses psychophysiological self-regulation to modulate the level of task engagement. Eighteen participants were assigned to three groups (self-regulation, false feedback, and control) and performed a compensatory tracking task that was cycled between three levels of task difficulty on the basis of the electroencephalogram (EEG) record. Those participants who had received self-regulation training performed significantly better and reported lower NASA-TLX scores than participants in the false feedback and control groups. Furthermore, the false feedback and control groups had significantly more task allocations resulting in return-to-manual performance decrements and higher EEG difference scores. Theoretical and practical implications of these results for adaptive automation are discussed.

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