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Special Feature

Effects of Automation Reliability and Training on Automation-Induced Complacency and Perceived Mental Workload

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The extensive use of advanced automated systems has created new concern for automation- induced complacency which is defined as inability to detect an automation malfunction. The present experiment examined the effects of automation training, automation reliability and workload on automation- induced complacency. 120 non-pilots participants operated a flight simulation task with several windows in which they have to detect automation malfunctions. The NASA-TLX was administered for the assessment of mental workload. A 2(training) x 3(reliability) x 2(session) x 3(block) mixed factorial design was used. Participants received either 30 min of short or 60 min of long automation training on low/mod/high automation reliability conditions, besides a common practice of 10 min on manual mode. Performances were recorded in terms of hits, false alarms and reaction time on system monitoring task and as root mean square errors on the tracking and on the fuel resource management tasks. Results showed that high static automation reliability increased automation-induced complacency and perceived mental workload reduced from pre- to post test sessions under high static reliability condition.

Keywords: Auto-reliability, Automation-induced complacency, Mental workload

Automation plays an increasingly important role in almost every domain of human life. Automation can be thought of as the process of allocating the activities to a machine or system to perform (Parsons, 1985). Wickens (1992) suggested three classes of automation that serve different purposes, viz, (i) automation can perform functions that are beyond the ability of humans or human operators who cannot perform them within a required period of time, (ii) automation can perform tasks that humans do poorly, and finally (iii) automation can assist humans by performing undesirable activities. Parasuraman and Riley (1997) defined automation as the execution of functions by machine (computer) which was previously carried out by a human.

Vigilance in an Automated World

The study of vigilance or sustained attention focuses upon the ability of observers to detect and respond to unpredictable events over extended periods of time (Ballard, 1996; Davies & Parasuraman, 1982; Warm, 1984, 1993). This aspect of human performance is an important concern for human factors/ ergonomic specialists due to the critical role that vigilance plays in many operational settings, especially those involving automated human-machine systems. Advancements in technology have transformed the role of observers from that of active controllers to system executives who monitor the functioning of machines that do the work for them and intervene only in the event of potential problems (Sheridan, 1970, 1980). However, this change in the role has made observers more complacent and over-dependent on automation. Consequently, vigilance is a critical component of human performance in a diverse array of work environments including military surveillance, air-traffic control, transportation security, nuclear power plant regulation, industrial quality control, and long distance driving (Hancock & Hart, 2002; Hartley, Arnold, Kobryn, & Macleod, 1989; Satchel, 1993; Warm, 1984, 1993). Vigilance also contributes to performance efficiency in medical settings, including x-ray and cytological screening and the inspection of anesthesia gauges during surgery (Gill, 1996; Warm & Dember, 1998; Weinger & Englund, 1990).

Although automation has reduced the information-processing load placed upon observers and has enhanced productivity (Parasuraman, 1987; Warm, 1993; Wiener, 1984, 1985), it appears to be a double-edge sword. Several studies have shown that accidents ranging in scale from minor to major are often the result of vigilance failure on the part of human operators (Molloy & Parasuraman, 1996). One solution to this dilemma would be to eliminate the need for the human component in automated systems. However, as Parasuraman (1987) has argued, a solution of that sort is not feasible because of the need for human operators to serve in a fail-safe capacity in the case of system malfunction. With this in mind, an understanding of the factors that influence vigilance performance and their underlying mechanisms is crucial for system integrity and public safety (Nickerson, 1992; Warm & Dember, 1998).

Automation had many beneficial effects on workload and safety. The ground-proximity warning system (GPWS) is a good example of the beneficial effects of automation on safety. It warns pilots when aircraft comes in close proximity to something similar to ground (e.g., close to mountains). Cockpit automation has made it possible to reduce flight times, increase fuel efficiency, navigate more effectively, and extend or improve the pilot's perceptual and cognitive capabilities (Singh, Sharma & Singh, 2005; Wiener, 1988). However, these advantages of automation have been achieved after enduring a number of costs like degradation of manual skills, and 'automation-induced complacency' (Parasuraman, Molloy & Singh, 1993).

Automation-induced complacency is a phenomenon which occurs if automation is highly but not perfectly reliable in executing decision choices, in such conditions the operator did not required to monitor the automation and its information sources and hence the operator may fail to detect the occasional automation failures. Singh, Molloy and Parasuraman (1993) conducted an initial study of the psychological dimension of 'automation-induced complacency' and suggested that complacent behaviour might be occurring only when complacency potential co-existed with other conditions such as (a) pilot inexperience with the equipment; (b) high workload brought about by poor weather, heavy traffic, or equipment trouble; (c) fatigue due to poor sleep or long flights; and (d) poor communication between ground and crew or among crew members.

Despite these costs, the operator prefers to use automation without completely withdrawing the human operator from such systems because it is a common belief that human beings are more flexible, adaptable and creative than is automation and thus, they are better equipped to respond to hanging or unpredictable conditions (Parasuraman & Riley, 1997). Therefore, these issues pertaining to human factors need to be addressed, while assigning full control authority to machine. Bruemmer, Marble and Dudenhoeffer (2002) observed a dramatic reduction in many types of human errors due to automation. However, automation itself has failed in many ways (Cook & Carbridge, 2000; Thurman, Brann & Mitchell, 1999). First, an automation aid can fail to produce a response or a signal message. Second, an automation aid may have a low accuracy due to technology limitation including over simplification of the underlying decision making models. Third, automation aids may work perfectly but fail to respond at the right time.

Automation reliability, trust and automation-induced complacency

Automation reliability has been usually defined as the number of correct operations done by computer out of the total number of operations. The automation trust is based on the assumption that users generally slacken their trust levels to accommodate different levels of automation reliability, although such changes in trust may not always be perfectly calibrated with changes in automation reliability. To date, however, few studies have attempted to test this assumption directly by comparing the effects of different levels of automation reliability on users' trust levels (Wickens & Hollands, 2000). Indeed, most studies have examined how trust develops when interacting with automation of a single reliability level, or how a solitary automation failure can affect users' trust of a system that has been completely reliable prior to the failure (Lee & Moray, 1994). Results of the studies that have systematically varied automation reliability levels are mixed, some suggesting that operators are sensitive to different levels of reliability (Parasuraman et al., 1993; Sharma, 1999; Singh, Molloy & Parasuraman, 1997; Singh et al., 2005) while others suggest that operators are insensitive to reliability differences (Dzindolet, Pierce, Beck, Dawe & Anderson, 2001). Automation reliability is an important determinant of human performance under automation mode because of its influence on human trust (Lee & Moray 1992; Masalonis & Parasuraman, 1999). Lee and Moray (1994) found that automation utilization of operators performing a simulated processing control task recovered rapidly after fault in the automation. However, verbal reports of trust dropped significantly after automation failure and took several trials of reliable automation to approach previous levels. In another study, Lee and See (2004) have noted that "below a certain level of reliability, trust declines quite rapidly. The absolute level of this drop-off seems to be highly system and context dependent with estimates ranging from 90% and 70% to 60%" (p. 72). Wickens, Gempler and Morphew (2000) demonstrated performance benefits in flight path prediction during traffic avoidance for 87% reliability. The level of reliability has an impact on operator's trust and subsequently human performance. However, imperfect automation does not always create absolute distrust. Several studies have examined the effects of imperfect or unreliable automation on operator performance in target detection and complex decision making tasks (Galster, Bolia, Roe & Parasuraman, 2001; Rovira, McGarry & Parasuraman, 2002). Results showed that operators have difficulties in detecting targets or making effective decisions, if the automation incorrectly highlights a low priority target or gives incorrect advice. Automation unreliability or low reliability may lower operator's trust and can therefore undermine potential system performance benefits of the automation. Similarly, Wiegmann, Rich and Zhang (2001) suggest that users of automated diagnostic aids are sensitive to different levels of system aid reliabilities.

Recently, Bailey and Scerbo (2007) assessed the impact of system reliability, monitoring complexity, operator trust and system experience on automation-induced complacency. The result suggests that for highly reliable systems, increasing task complexity and extensive experience may severely impair operators ability to monitor for unanticipated system states.

Training

Training is perhaps one of the most important issues relevant to automation-induced complacency. Automation can place conflicting demand upon pilots, with which they may not be well equipped to meet (e.g., passive monitoring versus active control) unless they have been specifically trained to cope with these demands. It has been suggested that inadequate training may lead to several automation-induced problems in the cockpit. For example, it has been reported that negative effect of automation on monitoring performance may be related in part to a lack of 'automation based' skills (Parasuraman, Hilburn, Molloy & Singh, 1991).

Training usually improves performance efficiency. The type and duration of training has also been discussed in relation to highly automated and reliable systems. Singh et al. (1997), examined whether automation-induced complacency could be overcome by central location of the automated task and were given 10-min of manual practice to their non-pilot participants. The results suggested that the centrally located monitoring task could not improve automated monitoring performance. This could be due to the short duration of manual practice which was not sufficient to develop monitoring skills, resulting in an automation-induced complacency. Moreover, Sharma (1999) studied the effects of manual training, automation reliability, personality and arousal on automation-induced complacency in flight simulation task. He reported that although increased manual training improved overall performance, length of manual training had no effect on automation-induced complacency. Similarly, Singh, Sharma, and Parasuraman (2000) investigated the effects of extended manual training on monitoring performance by varying the amount of manual training from 30 min to 60 min prior to the automated blocks. The results suggested that the increased amount of manual training did not reduce the automation-induced complacency. Moreover, complacency was significantly higher under constant reliability than it was under variable reliability.

Automation and mental workload

Mental workload is an important factor in use of automation. One of the fundamental reasons for introducing automation in complex systems is to reduce workload, and thereby to reduce human error. However, evidence shows that this is not necessarily true in all situations. Instead, Woods (1994) argued that automation merely changes how work is accomplished. Wiener (1989) has even claimed that in some instances the introduction of automation may increase the workload. He cautioned that too often automated systems might operate well under periods of low workload and become a burden during high workload periods. Mental workload is related to the concept of information processing which in turn is related to attention. Paying attention is difficult, especially for boring, monotonous and tedious tasks. It has been found that sometimes one is selective in focusing attention and in that process one ignores other related events. In today's fast-paced society, another type of attention viz., divided attention, predominates, which refers to the ability to focus attention on more than one event simultaneously (Lane, 1982; Wickens, 1984). The divided attention is a time-sharing phenomenon. This is a descriptive term because it implies sharing of mental resources. Although at times dividing attention among several tasks possibly results in less than optimal performance, the routine activities of most modern jobs demand constant reliance on divided attention. Thus, currently one of the most researched topics in human factors involves the allocation of mental resources in task performance. The basic idea behind mental workload is a comparison between a person's limited mental resources and the resources demanded by the task; another way to look at it is the information processing demands placed on a person by a task (Sanders & McCormick, 1993).

Automation has been designed with the objective to reduce operator's workload however, results suggested that automation does not necessarily reduce workload (Singh, & Parasuraman, 2001). Parasuraman (1999) pointed out that automation could reduce the human operator's workload to an optimal level, if it is suitably designed. Further, if automation is implemented in a 'clumsy manner', workload may not be reduced (Wiener, 1988).

Contrarily, Madigan and Tsang (1990) showed that automation could increase workload rather than to reduce it. It could be because firstly, automation may change the pattern of workload across work segments. Second, the demands of monitoring can be considerable (Parasuraman, Mouloua, Molloy & Hilburn, 1996). Braby, Harris and Muir (1993) reported that high levels of workload could lead to errors and system failure, whereas low workload could lead to complacency. Thus, it could be a reason for using automation in the first place to reduce high demands on the operator , resulting decrement in human error However, none of the researcher has attempted to examine the concomitant effects of extended automation training and automation reliability on monitoring of automation failures and workload.

There are a number of researches that serve empirical support for the outcome of automation-induced complacency and workload. Nevertheless, it has not been attempted to examine the associated effects of auto-training, automation reliability on the monitoring performance and workload in multi-task environment. Several researchers have reported the relationship for concise presentation periods after small or extended amount of manual training. Some studies have also suggested that automation ought to be designed with the objective to reduce operator's mental workload, and some other studies have suggested that automation does not necessarily reduce workload. In view of these controversial issues about the role of training, reliability and workload on the detection of automation failures an attempt has been made to examine the effects of extended training in auto mode and automation reliability on the relationship between monitoring automation failure (automation-induced complacency) and mental workload. We hypothesized that (i) the amount of automation training would reduce automation-induced complacency, (ii) automation-induced complacency would be progressively higher across the time periods for high static automation reliability and (iii) high static automation would reduce mental workload.

Method

Design:

A 2 (automation training) x 3 (automation reliability) x 2 (session) x 3 (block) mixed factorial design was used. Automation training and automation reliability were treated as between subjects factors, whereas session and block were treated as within subjects factors. The participants were assigned randomly to either short of 30 min or long of 60 min automation training groups under three levels of static (constant) reliability condition. Automation reliability was defined as the percentage of correct detection of malfunctions by the automation routine in each 10 min block in system monitoring task. The levels of static automation reliability conditions were low (25%), moderate (50%) and high (87.5%).

Participants:

120 non-pilots of Banaras Hindu University were randomly employed in this experiment. Each participant had normal (20/20) or corrected to normal visual acuity and their age varied from 19 to 22 years (mean age = 20.80 years). None of the participants had prior experience on the flight simulation task. Participants were randomly assigned in each of the four experimental conditions. Participants were informed on the general nature of the experiment for consent purpose, but were only provided feedback on their performance following completion of training. Each participant received 10-min manual practice on flight simulation task. Participants, who secured 60% and above on engine-system monitoring task performance, were selected for main experiment.

Tools:

Flight simulation task: A revised version of multi-attribute task battery (MAT: Comstock & Arnegard, 1992) was used in the present study. This is a multi-task flight simulation package comprising two dimensional compensatory tracking, engine-system monitoring, fuel resource management, communications, and scheduling. In the present study, only the engine-system monitoring, tracking, and fuel-management tasks were used, in which engine-system monitoring task was automated during test sessions (see Figure 1). These three tasks were displayed in separate windows on a 14" SVGA colour monitor of a PC-486 computer. (For details regarding the task see Singh, Sharma, & Singh, 2005; Singh, & Singh, 2006)

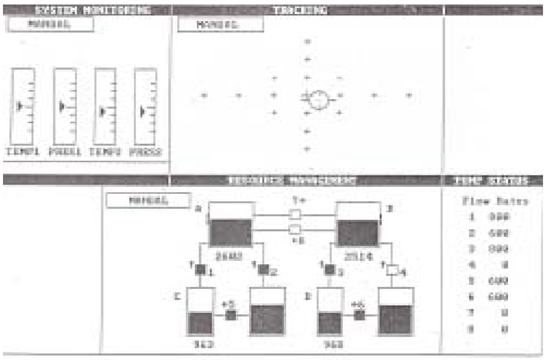

Figure 1. Multi Attribute Task Battery (Modified version)

*p < .05; **p < .01

NASA-Task Load Index Scale

The NASA-TLX (Hart & Staveland, 1988) was used for the assessment of workload on individual basis, which is considered as one of the most effective measures of perceived workload so far (Nygren, 1991). This scale has very high reliability (r = .83) and it has six sources of workload. Three of these sources reflect the demands operator (mental, physical, and temporal demand), whereas remaining three sources characterize the interaction between the operator and the task (performance, effort, and frustration).

Procedure:

Each participant received 3 min demo of flight simulation task to be familiar with the experiment and a 10-min of common practice, which served the purpose of selecting the participants in different experimental conditions. Out of 120 participants, 60 participants were given short automation training (30 min) and 60 participants were given long automation training (60 min) on flight simulation task. Feedback on performance for all three tasks was given to each participant after training. Participants were than required to perform final two 30 min task sessions. The automation reliability of monitoring task was static throughout sessions. All sixty participants further equally randomly assigned in each reliability condition i.e., low, moderate and high. Feedback on the tracking and on the fuel-management task performance was provided at the end of each test session. The performances in terms of hit rates, false alarms, reaction time and root mean square errors were recorded as dependent measures.

NASA-Task Load Index was administered individually to all participants once before and once after final test sessions. The participants rated each subscale one at a time on a bipolar rating system with the lowest score equal to 0 and the highest score equal to 100. In accordance with the procedures defined by NASA-TLX, each subject weighted the relative importance of each subscale. The 'traditional' NASA-TLX scoring procedure combines the six scales, using paired comparison-derived weight, to provide a unitary index of workload. Byers, Bitter and Hill (1989), however, demonstrated that a simple summation of responses on the six subscales produced comparable means and standard deviations, and that this 'raw' procedure correlated between 0.96 to 0.98 with the paired comparison procedure. Hendy, Hamilton and Landry (1993) also suggested that varying the rating does not add additional information to the sensitivity of the scale and a simple unweighted additive method can be used to combine ratings into an overall estimate. The NASA-TLX workload scale has high test-retest reliability (r = 0.83), which has been considered as one of the most effective measures of perceived workload (Wickens & Hollands, 2000). Thus in present study a simple unweighted additive method has been utilized for obtaining overall workload score.

Results

Automation training performance: Mean training performance (hits) under short of 30 min and long of 60 min indicated that monitoring of malfunctions varied from 60% to 80%, respectively. However, the difference was not significant. This trend of result was maintained for remaining other measures like false alarms, reaction time and root mean square performances. Thus, participants of both short and long training condition do not differ in terms of their cognitive skills achieved during training.

Automation task performance Correct detection performance: Means and standard deviations for correct detection of malfunctions on system monitoring task were computed for six 10 min automated blocks. Mean correct detection (hits) performance showed no difference between long automation training (M = 48.57; SD = 36.98) and short training (M = 49.25; SD = 35.15) condition. Moreover, participants detected more malfunctions in low reliability of static automation (M = 59.06; SD = 34.02) than moderate (M = 45.53; SD = 36.78) and high reliability condition (M = 42.12; SD = 33.49). Participants also performed better in the first 30 min (M = 50.59; SD = 35.89) than in the second 30 min session (M = 47.22; SD = 33.64). Thus, results indicated that the detection performance impaired over sessions. However, the mean hits performance under blocks demonstrated that monitoring performance was higher in the second block (M = 54.75; SD = 34.66) than in the first (M = 47.68; SD = 34.55) and in the third block (M = 44.29; SD = 35.07). Correct monitoring performance (hits) data were then submitted to a 2(automation training) x 3(automation reliability) x 2(session) x 3(block) analysis of variance with repeated measures on the last two factors.

The analysis of variance results showed that the main effect of training was non-significant, which revealed that the amount of automation training given prior to the detection of automation failures under constant reliability condition had no impact on 'automation-induced complacency'. It is thus apparent that this result does not support our first hypothesis that the amount of automation training would reduce automation-induced complacency. The main effect of automation reliability indicated that the participants performed significantly better in low constant reliability than they did in moderate and in high constant reliability condition. The interactions of automation reliability x session, block (see Figure 2), and automation reliability x block, were also found significant. Thus, analysis of variance revealed that high level of automation reliability impaired monitoring performance across sessions and blocks resulting automation-induced complacency. These findings supported the second hypothesis that detection of automation failures would progressively decline over time periods under constant reliability condition. These findings are also consistent with other researchers (Parasuraman et al. 1993; Singh et al, 1997).

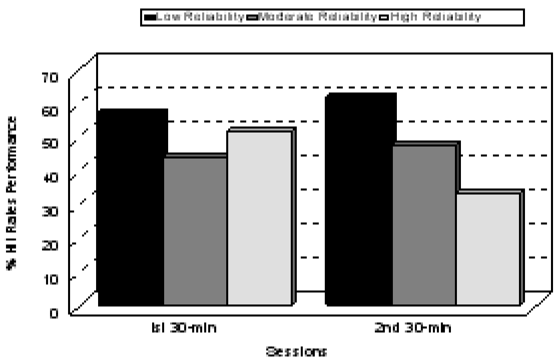

Figure 2. Hit performance as function of reliability levels and sessions.

False alarms performance: False alarms were relatively few in numbers and there was a trend of decrement in commission of errors in low reliability condition than in moderate and in high reliability. Moreover, a 3(automation reliability) x 2(sessions) x 3(blocks) analysis of variance gave no significant effects for any factor.

Reaction time performance: Reaction time could not be computed for each of the six 10 min blocks because some of the participants had 0% detection rates in at least one of the blocks in each of the experimental condition.

Tracking performance: Mean root mean square errors on the tracking showed no significant group diference. ANOVA results for tracking RMS errors were also not found to be significant.

Fuel resource management tasks performance: Mean root mean square errors on the fuel resource management t asks showed no significant group difference. None of the interaction was also found significant for fuel management RMS errors.

Automation and workload: To examine the third hypothesis that high static automation may reduce workload, causing low automated complacency, a paired t-comparison test was performed between before and af ter scores of each factor of ment al workload scale (NASA-TLX index), irrespective of training conditions. Results are graphically displayed in Figure 3.

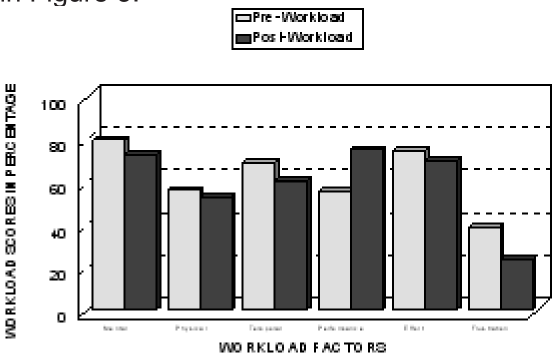

Figure 3. Workload scores at pre- and post sessions.

Means and standard deviations of each workload indices indicated that pre-ment al demand, pre-physical, pre-temporal demand, pre-effort and pre-frustration indices were high than in the post session. These mean differences were further comp ared by using paired t-test, since these workload scores were obt ained at two intervals of time i.e. before and af ter main t ask sessions. The obtained t-values are presented in Table 2. Results indicated that mental, temporal, effort and frustration workload reduced from pre- to post task session under constant reliability condition. Particip ant's performance also significantly increased from pre- to post session.

Table 1. Summary of t-test at pre and post-test sessions.

Paired Conditions	df	t-value
Pre-Mental WorkloadPost-Mental Workload	119	3.99**
Pre-Physical WorkloadPost-Physical Workload	119	1.35**
Pre-Temporal WorkloadPost-Temporal Workload	119	4.45**
Post-Performance Workload Pre-Performance Workload	119	-13.41**
Pre- Effort WorkloadPost-Effort Workload	119	2.66**
Pre-Frustration WorkloadPost-Frustration Workload	119	7.70**

p<.01

Discussion

Automation-induced complacency has been documented as one of the potential cause or a contributing factor in many aviation accidents for the last two decades. It is reported that the crews, who are working in highly reliable automated environments under multiple tasks environment in which they serve as supervisory controller monitoring system exhibit automation-induced complacency (Bailey & Scerbo, 2007; Parasuraman et al., 1993; Sharma, 1999; Singh, Parasuraman, Molloy, Deaton & Mouloua, 1998). Several reports have discussed the dangers of automation-induced complacency. However, little empirical research has been produced to substantiate its harmful effects on performance as well as some other factors that could be the cause for automation-induced complacency. The present study is an attempt to revalidate the findings of automation-induced complacency (Parasuraman et al., 1993; Singh & Parasuraman, 2001) and also to examine relationship between system reliability and mental workload. The results of the present experiment suggest that automation-induced complacency may occur in a multi-task condition where subjects are detecting automation failures under high static system reliability condition in comparison to variable system reliability condition. This effect of automation-induced complacency further increases across time periods. These findings support the second hypothesis that stated that automation-induced complacency would be progressively higher across the time periods for high static automation reliability.

The present findings related to performance consequences to automation-induced complacency provide a more potent empirical evidence for the flight simulation task as proposed by Wiener (1981). Some researchers (Thackray & Touchstone, 1989; Parasuraman et al., 1993) suggested that the automation-induced complacency can be obtained only in lengthy field studies with very few infrequent automation failures. In view of the above suggestion, the present experiment was conducted over six 10-min blocks with the expectation that automation-induced complacency would occur in the last few blocks.

The first hypothesis stating that the increased training under automation mode would reduce automation-induced complacency was not supported. It seems that training with high system reliability helped participants in developing more trust in the system, resulting in automation-induced complacency (Singh etal., 1993). This finding further supports the contentions of Bailey and Scerbo (2007) that the operator's trust can be increased as a function of increasing system reliability.

It is evident from the results of mental workload that automation may reduce workload to some extent which supports our third assumption that automation would reduce mental workload. However, big sample sizes are required to test under various levels of automation reliability to generalize the obtained finding that automation use may reduce mental workload. This result corroborates the finding of Singh et al. (2005) who reported significantly higher temporal workload between pre and post test session in short training than long training condition. Further they found significantly high degree of frustration workload in pre than post automated task performance in long training condition. This result also corroborates the finding of Metzger and Parasuraman (2005) who recently reported that reliable automation reduces mental workload.

The obtained results further suggest that the cognitive skills acquired through extensive automation training do not reduce automation-induced complacency in multi-tasks environment. Results further support that automation-induced complacency is a robust phenomenon and that it can be observed in multi-task environment while automation reliability is very high and unchanging (Singh & Singh, 2006).

Conclusion

The present results provide evidence that automation-induced complacency is a highly complex psychological construct within the field of aviation that warrants further study. The present results also demonstrate the critical need for developing strategies to ameliorate the performance consequences of automation-induced complacency. Lee and See (2004) have suggested that strategies related to the design and training associated with automated systems can help to facilitate human-automation interaction.

Another potential strategy facilitating human-automation interaction is through the use of adaptive automation. Adaptive automation refers to systems where the level, functionally and/or number of automated systems can be modified inreal time allowing for a restructuring of the task environment based on evolving situational demands (Scerbo, 1996). It has been suggested that this form of dynamic allocation of functions may represent the match between task demands and the cognitive resources available to an operator (Rouse, 1976; Parasuraman, Mouloua, Molloy & Hilburn, 1992). As such, the adaptive automation paradigm may help to enhance operator monitoring in automated systems as a result of improving attentional resources and enhancing the quality of information processing supporting task performance.

We think it is possible however, to suggest that if automation is brought in correctly, with the interaction between the operator and the automated process in mind, with the correct processes automated and at the correct level of automation, then positive results for human performance may be yielded. Mental workload may decrease, allowing greater situation awareness and thus a better mental model, which in turn will allow quicker detection of failures in both the system and the automation. Operators will be an active part of the system rather than a "machine minder" (Bainbridge, 1987) and as a result, will maintain the efficiency in retrieval of knowledge required along with being able to interpret the effect of their actions within the system of which they are a part. And so, although it is currently the case that in the majority of cases automation has actually had a detrimental affect on human performance, once the correct designs and implementations are used, this may no longer be the case.

Implications

The results of the present study are relevant to the debate on technology-centered versus human-centered approaches to the design of cockpit automation (Norman, Billings, Nagel, Palmer, Wiener & Woods, 1988). The dominant tendency of the former approach has been to implement automation whenever possible in order to reduce pilot workload and to reap the benefits of economies such as fuel efficiency, and reduced training costs. In the human-centered automation philosophy, the decision to use or not to use automation is left to the operator. If automation is to be used appropriately, potential biases and influences on this decision should be recognized by training personnel, developers, and managers. The high reliability of automated systems raises an issue: Does the fact that human monitoring is an inefficient matter, given that automated monitoring can be near perfect? The present findings suggest that it does matter when conditions likely to produce operator complacency are present, even if machine monitoring is very reliable. Many studies of joint human-computer performance have found that aided performance is generally better than human performance or computer performance alone (Parasuraman, 1987; Sorkin & Woods, 1985). The present results suggest that automated monitoring does not guarantee reliable system performance due to the potential for human monitoring to exhibit the consequences of automation-induced complacency. The problem of over-reliance on automation is also known to the aviation industry . An adaptive function allocation may provide possible countermeasures to automation-induced complacency (Parasuraman et al., 1992).

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