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Multi-Task Performance in Computer-Aided Systems: An Appraisal

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Computer-aided system or automation technology is a pervasive phenomenon, which confronts inexorably human issues of cognitive functioning. Automation envisages the thought of electronic replacement of human operator. It plays a critical role in situations when a small number of operators must control and supervise a very complex set of remote processes. The present review examines the notion of automated complacency and mental workload along with the factors, which promotes or confines the effective usage of automation by human operators. The concomitant effects of extended training, automation reliability and feedback on the detection of automation failures and perceived workload in multitask ambience have been studied and demonstrated in this paper. A long tenure of training administered to the subjects indicated no benefit in terms of monitoring efficiency and mental workload in the multitask ambience as well as results also deciphered that varying feedback types failed to diminish mental workload, causing detection inefficiency. The underlying mechanism of adaptive automation is also considered within the framework of psychophysiological (HRV, pulse rate, EEG) evidences.

Keywords: Automation, Complacency, Mental workload, Monitoring, Efficiency

Computer-aided system or automation in crude terms refers to those circumstances when a machine or a computer performs a task that is otherwise performed by the human operator. Automation may be defined as automatic handling of parts between progressive production processes. Automation also signifies, as ‘having equipment perform a function that could be performed by the pilot manually’ (Kantowitz & Sorkin, 1983). It can be further, thought of as the ‘process of allocating the activities to a machine or system to perform’ (Parsons, 1985). Moreover, Parasuraman and Riley (1997) defined automation as the execution of functions by machine (computer), which was previously carried out by a human. However, it is noteworthy that the more sophisticated it gets, the less people embrace it. Also, it is silent and opaque having no intelligence of its own as such. Now it is high time to realize that the motive of today’s human factors or cognitive research is to develop such systems, which provide the operator to work freely, thereby still maintaining the proficiency and support of automation. Henceforth, it is sagacious to consider uniform application of automation to every unit of the system need not be necessary and human interference at some extent might become inevitable.

Automation levels

The stages of automation can be encapsulated from the human information processing units that automation aims to replace or augment and the amount of cognitive or motor work that automation replaces which accounts for the level of automation. Parasuraman, Sheridan and Wickens (2000) defined four stages with different levels within each stage, for example, information acquisition, selection and filtering, information integration, action selection, and choice and control and action execution. It is evident that the levels of automation signifies the amount of "work" done by the automated component and thereby relieving the workload from humans. Parasuraman et al., (2000) suggested that automation could be applied to four broad classes of function: (a) information gathering (or acquisition); (b) information analysis; (c) decision and action selection; and (d) action implementation. Automation in each functional dimension can vary across several levels, i.e., from lower to higher levels. However, conventionally automation is based on a policy of allocation of function in which either human or machine has full control of a task (Fitt's, 1951). Fitt's also identified some of the superior attributes of man and machine in terms of power and control (see Table 1).

Table 1:The Fitt's List

Men (human) are better at:	Machines are better at:
1. Detecting small amounts of visual, auditory or chemical energy	1. Responding quickly to control signals
2. Perceiving patterns of light or sound	2. Applying great force smoothly and precisely
3. Improvising and using flexible procedures	3. Storing information briefly, erasing it completely
4. Storing information for long periods of time, and recalling appropriate parts	4. Reasoning deductively
5. Reasoning inductively6. Exercising judgment	5. Doing many complex operations at once

Benefits of automation

The aim of automated devices in aviation or any other domain speaks out its need to cater some of the multifaceted tasks, which is otherwise next to impossible job to accomplish. Also automation fosters for feasibility of technology and its low inputs from the architects of the technological advancements. Incorporation of automation in aviation industry made flying faster, safer and more economical. Automation is also considered to be more efficient, reliable and accurate than the human operator and it has been used at the highest possible level (Singh, Molloy, Parasuraman, & Westerman, 1994).

Problems of monitoring performance with computer-aided system

The benefits of automation have been achieved on the pretext of number of costs, for example, automation-induced complacency, mental workload, the loss of situation awareness, degradation of monitoring abilities and manual skills (Endsley, 1998; Singh, Parasuraman, Molloy, Deaton, & Mouloua, 1998; Parasuraman, Molloy, & Singh, 1993; Weiner, 1988).

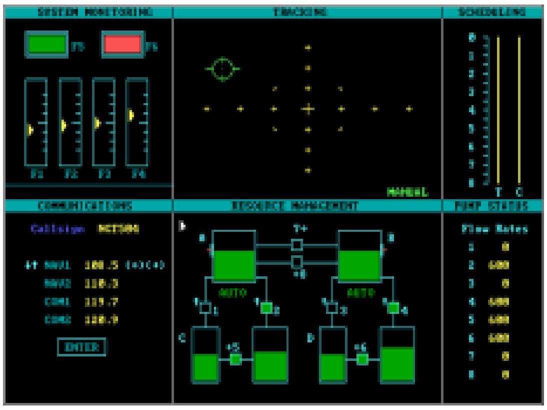
Automation-induced complacency

Over trust of automation is sometimes referred to as complacency, which occurs when people trust the automation more than what is warranted and can result in very severe negative consequences, if the automation is less than fully reliable (Parasuraman, et al., 1993; Parasuraman et al., 1997). Weiner (1981) defined complacency as "a psychological state characterized by a low index of suspicion" (p.117). Parasuraman, et al., (1993) argued that the element of workload is necessary for the development of automation-induced complacency. Perceiving the device to be of perfect reliability, a natural tendency would be for the operator to cease monitoring its operation or, to at least monitor it far less vigilantly than is appropriate (Bainbridge, 1983; Moray, 2003). This situation exacerbated by the fact that people make pretty poor monitors in the first place, when they are doing nothing but monitoring (Parasuraman, 1986; Warm, Dember, & Honcock, 1996).

Singh et al., (1993) suggested that determining the people's attitude toward automation might reveal the potential for complacent behavior. Regarding assessment of everyday automated devices like ATM's, automobile cruise controls, and laser technology, they developed a 20 item CPRS (Complacency potential rating scale) with very high internal consistency (r = 0.90) and test-retest reliability (r = 0.87) which established the major factors accounting for "complacent behaviors" viz. person's trust, reliability and confidence in automation. They further enunciated their findings by stating that complacent behavior is observable only when complacency potential co-exists with other conditions such as (a) pilot inexperience with 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. Thus the combination of the crew's attitude toward automation for instance overconfident and a particular situation like high workload might result in automation-induced complacency. Parasuraman et al., (1993) further proposed that complacency was different from boredom or low workload.

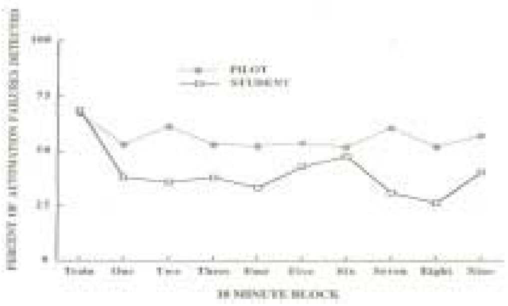
Parasuraman, et al., (1993) conducted two experiments pertaining to the human operator's detection of automation failure and for assessing the effect of variations in the reliability of an automated monitoring system. The first experiment involved 24 non-pilots, who performed a flight simulation task based on the modified version of the multi-attribute task battery (Comstock & Arnegard, 1992). The task comprised of engine system monitoring, two dimensional tracking and fuel resource management tasks (see Figure 1), and for four 30 min sessions, each consisted of 3 continuous 10 minute blocks, under constant and variable automation reliability conditions. Specifically, automation was programmed for system monitoring sub-task, while tracking and fuel resource management tasks were always manually controlled.

Fig1: Revised version of multi-attribute task battery



The percentage of malfunctions detected by the automation routine was referred to as automation reliability and it was varied between subjects. For the constant reliability group, automation reliability remained constant from block to block at a high level (87.5%; 14 out of 16 malfunctions detected) for half of the subjects and at a low level (56.25%; 9 out of 16 malfunctions detected) for the other halves. Also reliability alternated every 10-minute from low to high for half of the subjects and from high to low for the remaining subject's pertaining to the variable reliability group. Results detected that poorer monitoring efficiency occurred under the constant automation reliability condition compared to the variable reliability condition. In the second experiment, 16 subjects performed only the system-monitoring task in which they showed a high level of monitoring efficiency in a single task situation. Therefore, it was evidently the first empirical evidence of the performance consequences of automation-induced complacency and was observed in multitask ambience only. In the follow-up study, Singh, Parasuraman, Deaton and Molloy (1993), examined inefficiency in monitoring automated tasks and concluded that pilots operationally experienced similar automation induced-complacency in monitoring automation failures (see Fig.2).

Figure 2: Monitoring efficiency of pilots and non-pilots on flight simulation task



Earlier studies established that monitoring an automated task located in the periphery could lead to automation-induced complacency. Singh, Molloy, Parasuraman and Westerman (1994), experimentally established that location had no effect on "complacency" and inefficiency in monitoring automation was not necessarily due to reduced eye fixations to display location in the periphery. Thus, automation-induced monitoring inefficiency was noted, not due to visual scanning features but rather an attentional failure. Further, Singh, Molloy and Parasuraman (1997), propounded that automation-induced complacency is observed in static automation reliability rather than variable one. Thereby, the outcome of such results substantiated that the operator becomes complacent while monitoring automation malfunction under static automation over a longer duration of time.

Singh, Sharma and Parasuraman (2000a) considered the amount of training prior to monitoring the automated task and observed that monitoring efficiency significantly deteriorated during constant (static) automation as compared to variable over time periods. In the follow up study, Singh, Sharma and Parasuraman (2000b) investigated the effects of extended training on monitoring performance by varying the amount of manual training (30 min of short and 60 min of long manual training) to the automated blocks. Manual training signifies that the participants performed the three simultaneous tasks viz., System Monitoring, Tracking and Fuel Resource Management manually. However, their study revealed that an increased amount of manual training failed to reduce automation induced complacency. Moreover, complacency was significantly higher under constant reliability than it was under variable reliability (see Figure 3 & 4). Thus, the full-bodied existence of automation-induced complacency can be observed in a dynamic ambience under static automation reliability.

Figure 3: Automation-induced complacency after 30-min manual training

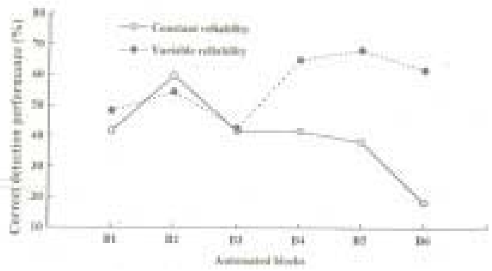
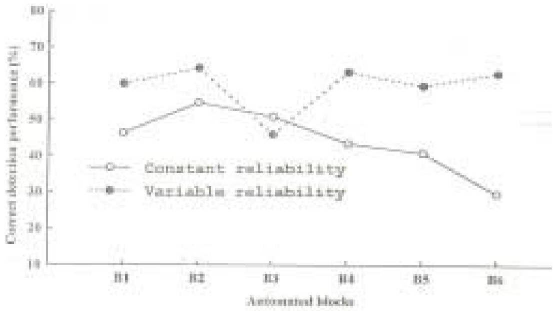


Figure 4: Automation-induced complacency after 60-min manual training



Mental workload and monitoring inefficiency

Mental workload pertains to information processing load or resource demands imposed by a task. It has also been defined as the "costs" of a human operator while performing complex tasks. This cost may be conceptualized as an undifferentiated capacity or resource (Kahneman, 1973; Moray, 1967). Introduction of automation aims at reducing operator's workload. Furthermore, the reduced workload achieved by automation could also pave the way for loss of situation awareness, as the operator was not actively involved in choosing the actions recommended or executed by the automation. According to Endsley and Kiris (1995), suggested a correlation between situation awareness and mental workload, as automation level moves up the scale, both workload and situation awareness tends to slag down.

The assessment of mental workload may be classified into three groups: behavioral, psychophysiological and subjective judgment (Desai, 1999). Braby, Harris and Muir (1993) reported that high levels of workload could lead to errors and system failures, while low workload could lead to complacency. The rationale could be that automation reduces the high demands at first place on the operator, resulting in decrement of human errors. The findings further enunciated that high automation often redistributed rather than reducing the workload within the system (Lee & Moray, 1992; Parasuraman & Mouloua, 1996; Singh & Parasuraman, 2001; Wiener, 1988).

It is reasoned that automation sometimes poses high demand and that become difficult to cope or manage, and which may require more attentional resources. Some of the studies have looked into the effects of automation and workload on monitoring/ tracking performance. The concomitant effects of extended training (manual & automated), automation reliability levels and feedback types on the detection of automation failures and perceived workload in multitask ambience was assessed by I. L. Singh, A. P. Singh, Dwivedi and A. L. Singh (2005). The three consecutive studies examined the effects of extended automation training, static automation reliability and performance feedback on perceived mental workload and automation-induced complacency. A 2(training) x 2(session) x 3(block) mixed factorial design was used for the first experiment in which training was treated as between subject factors, while session and block were treated as within subject factors. The flight simulation task comprised system-engine monitoring, compensatory tracking and fuel resource management tasks. The correct, incorrect detection and RT were recorded as the dependent performance measures for the system monitoring task and the RMS errors were recorded for the tracking and the fuel management tasks. Mean detection performance showed higher hits rate in long training than short training. However, mean difference on correct detection under two training was not significant, which revealed that the amount of manual training given prior to the detection of automation failures did not influence subjects monitoring detection efficiency. The main effects of session and block showed significant decrement in the detection of automation failures over sessions and across blocks. Furthermore, long training indicated benefits in terms of reduced workload than short training.

In the successive study (second study), they examined the effect of the increased automation training and automation reliability levels on system engine monitoring performance and mental workload. Automation training and automation reliability levels were treated as between subject factors. Similar MAT battery and NASA-TLX mental workload scale were used in this study. The performance measures were the same as recorded in the previous experiment. Mean monitoring performance showed no effect of the amount of automation training. Additionally, automation reliability levels significantly affected detection performance. Results indicated that all components of workload i.e., mental, temporal, effort, performance and frustration predicted significant mean difference between pre- and post workload indices, except physical workload. Thus, such outcomes propounded that monitoring automated task under multiple task condition significantly reduced temporal, effort, frustration and mental workload from pre- to post task session.

In continuation with above research establishments, the effect of performance feedback on perceived mental workload and system-engine monitoring task performance was observed in the subsequent third experiment. Correct detection performance on automation failures of the system-monitoring task revealed no feedback effect. Moreover, the main effect of session and a two-way interaction between sessions by feedback showed significant effect on monitoring performance, while remaining interactions were observed to be not significant. Furthermore, mean effort workload component showed significant difference between pre- and post session at successful feedback condition, which revealed that subjects perceived significantly low effort after getting successful performance feedback, while on the other hand subjects perceived significantly higher performance workload from pre- to post session after receiving failure feedback performance. It is noteworthy that none of the other workload factors was found significant between pre- and post sessions. In sum, the results suggested that feedback types failed to reduce mental workload across sessions, causing automation-induced complacency, thereby establishing the fact that automation-induced complacency is a robust phenomenon and observable in multi-task ambience (for e.g., aircraft cockpits, nuclear stations and railway track monitoring) while automation reliability is very high and static.

Physiological correlates (HRV and EEG) of mental workload

Evidently as task demands of air traffic control or pilots and crewmember increases beyond a threshold, operators might experience a condition of “overload”; thereby tasks cannot be accomplished in a fruitful manner. However, if a monitoring system can be developed to accurately assess an operator’s mental workload state, it could ease the accomplishment of required tasks and potentially save valuable property and lives. A primary benefit for use of brain mappings to infer mental workload is that electroencephalogram (EEG) offers good temporal resolution of cognitive activity with resolution well under a minute and can be used as one of the most direct, nonintrusive measures of the central nervous system (CNS). Also the peripheral measures, including eye blinks, heart rate, and respiration can augment EEG features with additional salient information. In general, eye blink rates decreases as visual demands increases, heart rate increases with increased workload demands while respiration inter-breadth intervals decreases with increase in mental demands. Such an approach is praiseworthy because by identifying a set of salient features, the “noise” in a classification model can be reduced, thereby resulting in more accurate general classification for external validation of data. At higher levels of workload, the heart rate (inter beat interval) tends to be more constant over time, whereas at lower workload levels it waxes and wanes at frequencies of around 0.1 Hz and those driven by respiration rate (Tattersall, 1992). Further, measures of visual scanning and other physiological workload measures like blink rate, pupil and diameter are also useful in understanding the qualitative nature of workload changes.

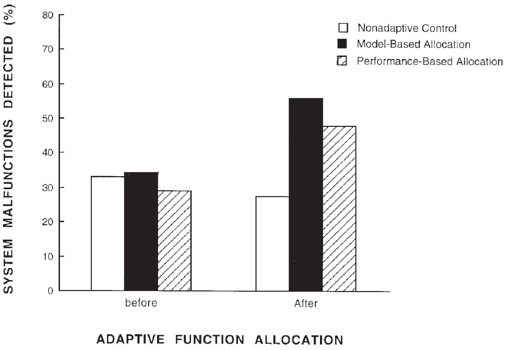
Psychophysiological recordings owe to the experimental manipulations of biological features for monitoring brain functioning. Traditionally the idea envisages from the arousal theory - the thought that the variability in brain functioning occurs from states of deep sleep through normal wakefulness to extreme excitement. It is observed that arousal may be assessed through CNS measure (EEG) and ANS (autonomic nervous system) measures like increased skin conductance and heart rate. ERP waves or components are usually labeled in terms of their polarity and the length of time that has expired since the initiating event: P300 is a positive component that occurs approximately 300 ms after an event. Experimental manipulation of stimuli and cognitive demands show how the components may be linked to particular types of processing (Luck & Girelli, 1998). Imperatively, there are physiological costs associated with the performance of cognitively demanding tasks. However, it is improbable that this “cost” arises only from the physiological “cost”.

Hybrid technology(Adaptive automation)

Allocation of functions between human and automation varies with time depending on the human’s workload as well as the current context. The risk of over-reliance in automated systems is an indicator for gradual decline in manual skills (Singh et al., 1993). Without practice, people lose their ability to react effectively when an emergency arises. You have to keep humans in the loop, honing their skills (Wickens, 1998). That’s where ‘adaptive automation’ creeps in. Adaptive systems, in which function allocation is flexible and responsive to task or operator demands, are thought to be less susceptible to automation-induced difficulties in monitoring or situation awareness (Parasuraman et al., 1990). The proponents of adaptive systems or the hybrid technology asserts that the benefits of automation can be maximized and the costs minimized, if tasks are allocated to automated subsystems or to the pilot in an adaptive, flexible manner rather than in an all or none fashion (Rouse, 1988).

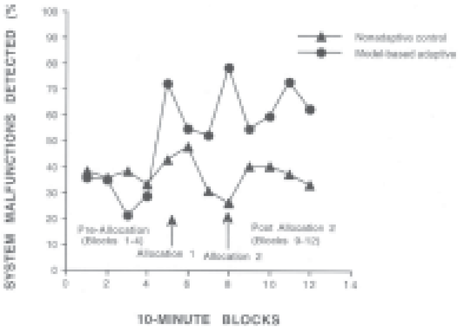
Mouloua, Parasuraman and Molloy (1993) further enunciated the notion by examining the effects of allocating the systems monitoring task to the operator for a brief period of time to subsequent monitoring performance with automation. Subjects performed the MAT flight simulation task under constant reliability (87.5%) through out the sessions. Two adaptive logics i.e., model and performance was manipulated in this study. The model-based adaptive group was allocated a single 10 min block of fully manual performance on the system monitoring task in the middle of the second session (i.e., on block 5). The performance based adaptive group was allocated fully manual monitoring in the middle of the second session but only if the average performance during the first 40 min was below 55% (performance criterion). Incase of both adaptive groups, the change in allocation was signaled 30 s prior to the change by a tone and by a visual message appearing in the display window. Also, following 10 min of manual performance in block 5, a pre-warned re-allocation of the monitoring task to the automation routine was administered. Automation was implemented for the rest of the session (block 6 through 9). The results supported the prediction that adaptive allocation of a task to the operator would result in improved monitoring performance of automation failures in subsequent blocks. The detection rate of automation failures was not significantly different for the three groups for the first 40 min (blocks 1-4) of automation. The mean detection rate was higher in the post allocation than in the preallocation phase for both adaptive groups (see Figure 5). The performance benefit was approximately the same for both methods of function allocation, 21.8% for the model-based group and 21.4% for the performance based.

Figure 5: Effects of adaptive function allocation on monitoring performance



Similarly, Singh, Parasuraman, Deaton and Molloy (1993) extended previous study of Mouloua et al., (1993) and examined that whether multi-adaptive function allocation would sustain performance benefits over prolonged automation periods in U.S. pilots. They used only model based adaptive function allocation method. The detection rate of automation failures was averaged across two manual allocation phases. Monitoring performance under automation or pre-allocation was lower than during manual allocation and post allocation phases. However, the performance levels (system malfunction detection) during manual allocation phase did not differ significantly from post allocation phase following the return to automation (see Figure 6). After assessing the comparison of the means of the pre-allocation and post-allocation phases, it was propounded the detection rate of automation failures was statistically significant and the performance benefit (29%) sustained over a longer automation period resulted from repetitive function allocation.

Figure 6: Pilot performance with multi-adaptive function allocation on monitoring performance



Human-centered verses technology-centered system

Automation has greatly improved safety, comfort and job satisfaction in many applications and is vindicated only when performance is enhanced and cost is reduced. Automation plays a critical role in circumstances when a small number of operators must control and supervise a complex remote process. Automation here is not "optional", it's a necessity (Sheridan, 2002). Ideally, the automation design should focus on creating a human-automation partnership by incorporating the principles of human-centered automation (Billings, 1996). The six human-centered automation features that are believed to achieve the goal of maximum harmony between human, system and automation are as follows: (a) Keeping the human informed; (b) Keeping the human trained; (c) Keeping the operator in the loop;

(d) Selection of appropriate stages & levels incase of imperfect automation; (e) Making the automation flexible & adaptive; and (f) Maintaining a positive management philosophy.

Evaluating automation totally in terms of technological issues is not enough primarily because there are many subtle changes in human decisions, which cannot be placed under technical umbrella. Performance of human's specific to their cognitive abilities and motor skills viz., speed and accuracy are imperative to analyze. It was believed that the pilots as per instructions enlisted in the help books would follow the products designed by the adept designers. However, this adaptation has been much more difficult than expected. The human speed pertaining to response stands out to be empirically limited. So these restrictions create a loophole in perfection and performance regarding the automated settings. Further, accuracy is another factor which accounts for perfection in human performance of automated devices or systems. Due to cognitive limitations and other job pressures (mental workload), accuracy might be a tradeoff, which affects the overall performance of the concerned authority. The cautions do not signify that automation is a bad monitor. As we have seen, many of the safety-enhancing possibilities are clearly evident. But automation must be carefully introduced within the content of a human-centered philosophy. And the promising approach is adaptive automation in which sensors monitor the users for signs of fatigue, distraction and other job related tasks and adapt vehicle control, information attainment and warning system accordingly.

Conclusion

After the description of an interlinking set of cognitive phenomena's pertaining to automation-induced complacency, mental workload, attention and task control, it necessitates viewing all these elements in consonance with each other. The psychophysiological evidences augment such imperative needs to comprehend these robust phenomena of psychological and ergonomic importance. Additionally, it becomes imperative to consider or ascertain the impact of powerful but imperfect computer aided systems or automation on pilot's workload, situation awareness and management of multiple tasks. The modern human factors approach is based on the result of task analysis and cognitive modeling, and the essence looms over the final query of human in command. Further, research and conceptual analyses are desirable to approach these factors of implementing effective human centered automaton too. It is simply true that performance has been improved with automation, and that safety measures have strengthened, even though better safety is always desirable.

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