Implementing Adaptive Function Allocation

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Adaptive function allocation, in which the control of tasks dynamically shifts between humans and machines, has been proposed as an alternative to traditional static allocation, in which task control is assigned during system design and remains unchanged during operations. Understanding adaptive allocation and its effects on operator performance and workload is limited by sparse systematic research and an underdeveloped theoretical framework for implementation. The purpose of this research was to determine the efficacy of adaptive allocation by implementing adaptive allocation in a multiple task aviation simulation based on a taxonomy with facets of invocation philosophy and allocation strategy. Pilot performance was evaluated to determine benefits and costs for the implementation of adaptive allocation in a multitask aviation simulation with tracking, system monitoring, and target identification tasks. The results provide support for the implementation of adaptive allocation based on a hybrid model comprising elements of operator performance and mission relevant variables. Implementation of adaptive allocation was an effective countermeasure to the predictable decrease in tracking performance associated with the initial presentation of a surface target. Benefits were also identified for monitoring task performance despite the fact that the monitoring task was not modified by the implementation of automation. Secondary benefits included improved time estimates. Potential costs of adaptive allocation included performance variability in the tracking when task partitioning was the adaptive strategy. Implications of results for design, philosophy, and theory are presented.

Early in the design of complex human–machine systems, conscious design decisions are made that determine the extent to which a given job, task, function, or re-

sponsibility is to be automated or assigned to human control. This fundamental area of human factors, the division of work between people and machines, is formally called function allocation (FA). FA has often been touted as the central principle of effective system design. Kantowitz and Sorkin (1987) noted that designing work that other people must perform is a grave responsibility. Meister (1987) observed that FA is the essence of design because it involves conceptualizing alternative ways in which systems, equipment, and personnel function. Wiener (1950) concluded that allocation of function was linked to aspects of human worth because, ultimately, it defines human roles, jobs, and responsibilities.

TRADITIONAL FA

The traditional process of FA is to compare the capabilities of humans and machines, usually by developing lists, and allocating tasks based on this comparison. This technique was first presented by Fitts (1951) who developed lists of machine and human capabilities in response to the question "What roles can the human (or machine) be assigned in future systems?" Roles were suggested based on what psychologists knew, at that time, about the limiting characteristics of human capacity and performance. Despite warnings that the suggested roles may be neither equally feasible or desirable, the listing technique was immediately taken as a design process and considerable subsequent effort has been devoted to developing further lists of human and machine capabilities (for comprehensive examples, see Bekey, 1970; Chapanis, 1965; Edwards & Lees, 1974; Meister, 1985; Mertes & Jenny, 1974; Swain & Guttman, 1980). Unfortunately, efforts in developing listed capabilities have largely been academic exercises in the development of explanatory frameworks, producing significant frustration for practitioners who claim that FA has limited usefulness in the practical design of systems (Fuld, 1993). Fuld claimed that there is scant evidence anywhere that the practice of formal FA has done much to improve the design of large-scale complex systems despite its enthronement as part of the conventional wisdom of the human factors profession over the last 40 years.

Hancock and Scallen (1998) reviewed the history and development of FA and identified numerous sources for its failure. The conclusion was that the failure of traditional FA can be ascribed to three sources. First, there is a general misunderstanding and misrepresentation of the Fitts (1951) report—probably due to the fact that like many "classics," it is more often cited than read. The goals, objectives, and limitations of Fitts are rarely acknowledged, especially with respect to the now famous Fitts-type lists. Without an understanding of the context of their presentation, these lists have been interpreted as a basis for design recommendations, although they were only intended to stimulate research and thinking on human–machine capabilities.

A second source of failure of traditional FA lies in the process itself: the static and dichotomous listing of capabilities. Traditional FA is acontextual (i.e., insensitive to the influence of environmental variables). With the ascendance of ecological psychology and the ecological approach to perception (see Gibson, 1966, 1979/1986), we now recognize that environmental context and constraints are essential sources of influence (see Chapanis, 1960; Flach, Hancock, Caird, & Vicente, 1995). To emphasize the influence of context, Young and McNeese (1995) examined three real-world, complex, problem-solving situations (i.e., surgery, piloting, and engineering design) and highlighted 10 important characteristics of situated problem solving (e.g., the information, discourse, technology, and atmosphere of an operating room). These authors demonstrated that problem solving must be viewed as a product of the interactions between neurological processes and environmental information perceived by the individual. We also recognize that "energetic" aspects of human behavior—those that encapsulate the affective components of behavior, such as stress, fatigue, workload, and situational awareness (see Freeman, 1948; Hockey, Coles, & Gaillard, 1986)—frequently mediate human performance. Price (1985) criticized traditional FA for not addressing emotional and affective requirements, such as the human need to know that work is recognized for its value, to feel personally secure, and to feel in control. Traditional FA also fosters comparison to the exclusion of complement, promoting task division rather than cooperation (Chapanis, 1965; Jordan, 1963; Price, 1985). Unfortunately, there are few efforts to develop theories and principles of task sharing (although see Grote, Weik, & Wafler, 1996; Licklider, 1960). Traditional FA has also been limited by the ascendance of the information processing paradigm. Regarding the brain as a calculating engine with programs and hard wiring (Hoffman, Cochran, & Nead, 1990) has biased traditional terminology to favor the machine (Hoffman, Feltovich, & Ford, 1997). Human abilities are couched largely in information terms that are actually far better suited to the description of machine abilities rather than the description of human abilities (Birmingham & Taylor, 1954; Fitts, 1951; Hopkin, 1980). For example, *computational speed* is a readily accepted benchmark in computer processing and is, thus, more readily viewed as a machine strength. However, if by computational speed we consider inductive reasoning, the capability becomes a human strength.

A final source of failure lies in what traditional FA produces: extended periods of human or machine control. Active human control over extended periods is associated with increase in error and onset of fatigue and reduced effectiveness. There is also a rich history of vigilance and sustained attention research that indicates that humans in a passive role are notoriously poor at remaining aware and alert to stimuli for prolonged periods of time (Parasuraman, 1987; See, Howe, Warm, & Dember, 1995). Concerns and issues of machine (automated) control have also been well documented in the human factors literature (see Mouloua & Parasuraman, 1994; Parasuraman & Mouloua, 1996; Parasuraman, Mouloua, Molloy, & Hilburn, 1996;

Warm, Dember, & Hancock, 1996; Wise, Hopkin, & Smith, 1991). Informative examples exist for surface transportation (Hancock, Parasuraman, & Byrne, 1996), rail transportation (Sorkin, 1988), nuclear power plants (Woods, O'Brien, & Hanes, 1987), manufacturing (Drury, 1996; Meshkati, 1996), maritime operations (Lee & Sanquist, 1996), medicine (Guerlain et al., 1996), office environments (Czaja, 1987), and telecommunications (Brems, Rabin, & Waggett, 1995; Katz, 1995)

FA IN AVIATION

Concerns for human use of automation in aviation and air traffic control have been well documented (Endsley & Kiris, 1995; Hopkin & Wise, 1996; Kirlik, 1993; Sarter, 1996; Stein, 1983; Wiener, 1985, 1988, 1989; Wiener & Curry, 1980; Wise et al., 1991). In fact, the role of automation in aviation has always enjoyed a certain notoriety in popular culture. The reliance on advanced systems and the tendency for aviation technology to filter down to other domains has placed human use of aviation automation squarely in the popular media. Human interaction with automation remains a popular topic with extensive efforts to develop comprehensive lists of verified flightdeck automation problems, new taxonomies for human use of automation, and new factors involved in allocation decisions like trust (Lee & Moray, 1992), confidence and mental workload (Riley, 1994), attitude (McClumpha & James, 1994), complacency (Parasuraman, Molloy, & Singh, 1993), and cognitive overhead (Kirlik, 1993).

Aviation also serves as the preeminent example of how the emergence of automated capabilities has diminished the active human role. Billings and Woods (1994) showed that the complexity of automation has progressively increased since the 1920s but at the cost of decreasing direct pilot control of the aircraft. Words like "peripheralized" and "insulated" are now common in aviation literature. Extended removal of pilot control, sometimes referred to as the "out-of-the-loop performance problem," has also received considerable attention (Billings, 1989; Billings & Woods, 1994; Endsley & Kiris, 1995; Moray, 1986; Wiener, 1988, 1989; Wiener & Curry, 1980) including concern for the deterioration/loss of skill (Wiener, 1989) and, more recently, the loss/impairment of situational awareness (Endsley & Kiris, 1995).

If traditional FA has contributed to the peripheralization of the pilot, frustrated human skill development, exacerbated already poor human-automation interfaces, and weakened our general understanding of the human role in aviation systems, should we simply abandon it? We argue that this would not be a wise course. To deny that pilots and aviation systems have respective strengths and weaknesses is to throw away valuable and hard-won information. Traditional FA can still be used to direct thinking toward aviation problems and to remind us, in general terms, of some of the characteristics that humans and machines have as aviation system

components (Chapanis, 1965). However, for aviation research to respond to the challenges of the future, FA must also change.

ADAPTIVE FA

One alternative to traditional FA is adaptive function allocation (AFA; Hancock & Scallen, 1996, 1998; Morrison & Gluckman, 1994). In AFA, the control of functions shifts between humans and machines dynamically, based on specified thresholds for environmental factors, operator competence, or psychophysiological factors. For example, an aviator would perform a continuous control task until some performance criteria were violated, as might be expected after extended continuous performance. After a violation, the machine (automation) would assume control of the task and return control to the aviator after a rest period. If the performance criteria were never violated, automation would never assume control. AFA does not deny the difference in human–machine capabilities. Rather, it seeks to take extensive and efficient advantage of these differences through a strategy that allows the momentary, daily, monthly, or even yearly changes in allocation to occur.

Implementing Adaptive Allocation

Existing research on adaptive allocation can be broadly classified into three categories. The first category includes discussion and commentary that identify critical human performance issues related to adaptive allocation and adaptive systems in general, such as the architecture and workload dynamics in adaptive interface design (Hancock & Chignell, 1987, 1988; Hancock, Chignell, & Lowenthal, 1985). The second category includes the empirical investigation of specific issues and phenomena thought to be relevant to the AFA framework. This includes research examining effects associated with cycling automation episodes (Hilburn, Molloy, Wong, & Parasuraman, 1993; New & Corso, 1996; Scallen, Hancock, & Duley, 1995), automation induced complacency (Molloy & Parasuraman, 1996; Parasuraman et al., 1993; Parasuraman, Mouloua, & Molloy, 1994), interface configuration (Hancock, Duley, & Scallen, 1993; Hancock, Scallen, & Duley, 1993), control of adaptation (Hancock, Duley, & Scallen, 1994; Hilburn et al., 1993), allocation strategy (Gluckman, Carmody, Morrison, Hitchcock, & Warm, 1993), task load and task load increment (Hancock & Williams, 1993), and task specific effects associated with automation failure (Carmody & Gluckman, 1993). As a whole, this research has identified many facets of the adaptive allocation framework that need further empirical examination. Of particular importance is the work of Parasuraman and colleagues who provided valuable empirical evidence for automation-induced complacency.

The third category of AFA research involves the systematic empirical evaluation of adaptive allocation based on facets of an implementation taxonomy. Scerbo (1996), building on the work of Morrison (1993) and Morrison, Cohen, and Gluckman (1993), developed a taxonomy for the implementation of adaptive automation (see Figure 1). The taxonomy enumerates adaptive allocation methods based on three dimensions: the philosophy of allocation invocation, the strategy of how pilot task demands should be adjusted, and the stability of the decision being made by the pilot. Although limited in number, research that examines facets of this taxonomy provides the strongest impetus for continued efforts to examine adaptive allocation. For example, Parasuraman, Mouloua, and Molloy (1996) examined invocation procedures and demonstrated that both performance-based philosophies and model-based philosophies (hybrid of more than one triggering algorithm) of adaptive allocation were effective countermeasures to performance inefficiencies. A study by Parasuraman et al. (1994), using pilots as participants, produced similar findings. In a review of invocation philosophies, Hancock and Scallen (1998) and Parasuraman, Mouloua, and Molloy (1996) suggested that hybrid invocation philosophies may hold the greatest potential for the effective implementation of AFA. In other work, Prinzel, Scerbo, Freeman, and Mikulka (1995) demonstrated that human state (specifically, electroencephalography [EEG] index) can be employed as an adaptive invocation philosophy. These researchers demonstrated that it was possible to moderate an operator's level of engagement through a
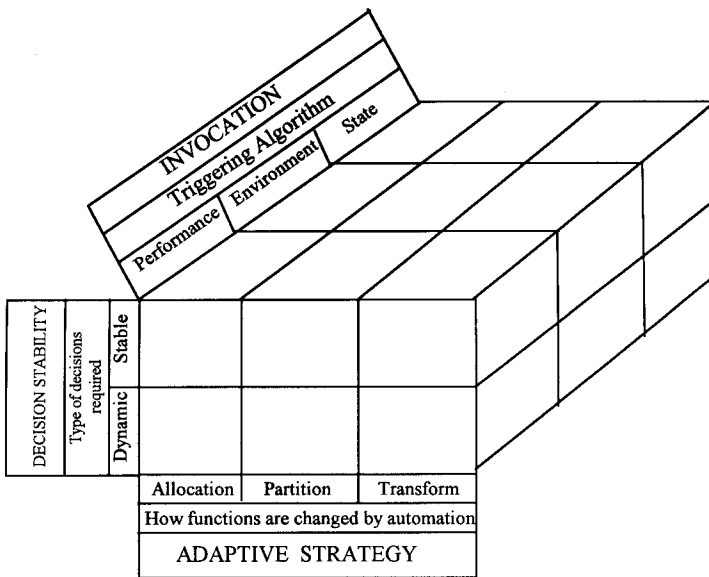

FIGURE 1   Taxonomy for the implementation of adaptive allocation (after Morrison, Cohen, & Gluckman, 1993; Scerbo, 1996)

closed-loop system driven by the operator's EEG. In addition, the system was sensitive to increases in task workload. Byrne and Parasuraman (1996) provided an excellent review of the role of psychophysiological measures in the study of adaptive automation and presented empirical results demonstrating how these measures may prove useful in the prevention of performance deterioration in underload conditions. Scerbo, Ceplenski, Krahl, and Eischeid (1996) and Krahl and Scerbo (1997) demonstrated that task partitioning was a viable option when implementing adaptive systems. Unfortunately, systematic and empirical research examining adaptive strategies is extremely underrepresented in aviation literature.

Problem and Purpose

Adaptive allocation has been proposed as an alternative to static allocation, with several proposed benefits. However, understanding adaptive allocation and its effects on operator performance and workload in multiple task systems is limited by sparse systematic research and an underdeveloped theoretical framework for implementation. The purpose of this research is to determine the efficacy of adaptive allocation by implementing adaptive allocation in a multiple task aviation simulation based on a taxonomy with facets of invocation philosophy and allocation strategy. Subtask performance and subjective workload will be evaluated to determine benefits and costs for the implementation of adaptive allocation in complex systems.

EXPERIMENTAL METHOD

Apparatus

The STARFIRE (Strategic Task Adaptation: Ramifications for Interface Relocation Experimentation) adaptive allocation test platform was used. To conduct experiments employing adaptive allocation, a test platform had to be developed that supported adaptive transfer of task control in a multitask environment. The goal was to develop a multitask battery with flight relevant tasks that, unlike other multitask platforms (see Comstock & Arnegard, 1992), captured relevant visual dynamics of flight. A new test platform, STARFIRE (see Figure 2), was designed and developed for this research initiative (see Hancock & Scallen, 1997; Scallen, 1997, for descriptions). Briefly, STARFIRE is a multitask flight simulation that requires the pilot to perform three flight tasks concurrently. STARFIRE combines flight relevant tasks with dynamic movement over a 3-D textured environment—a critical component for evoking the feel and richness of low-altitude tactical flight. The three subtasks can be performed singly, in combination, or under varying modes of automation as required by experimental procedures. STARFIRE is
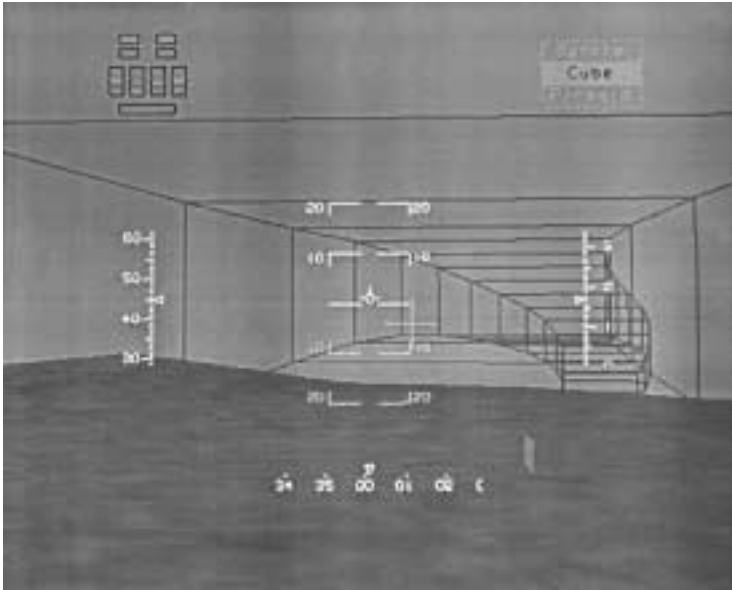
FIGURE 2   Strategic Task Adaptation: Ramifications for Interface Relocation Experimentation adaptive allocation test facility. The figure depicts the projected highway-in-the-sky over the textured surface. Head-up display (HUD) information includes speed (left), heading (bottom), and altitude (right) and dynamic pitch indicator (center). The tracking task requires pilots to align the nosepoint symbol with the crosshair as the pilot moves down the pathway (note that the alignment is depicted high and left). The monitoring display is located in the upper left corner. The monitoring task requires the pilot to respond to deviations from normal status (note that the indicator line of the second gauge is depicted deviated). The targeting menu is located in the upper right corner. The monitoring task requires the pilot to scan the surface for targets, activate a screen-based menu, and select the menu option that corresponds to the surface target (note that there is a cube target in the lower left corner, and the corresponding menu option has been activated).

supported on a Silicon Graphics 4D/310 VGXT Iris computer and displayed on a 35-in. Mitsubishi color monitor mounted in front of the windscreen of a single engine aircraft shell. The aircraft instrument panel is equipped with a four-axis, self-centering flightstick and numerous response and control buttons.

STARFIRE tasks.   The tracking subtask (tracking) is located centrally on the HUD. The tracking employs a 3-D pathway-in-the-sky that serves to guide the pilot along a preselected route with turns, ascents, and descents in all axis. The pathway is redrawn each second and presents a 10-sec lead. The task goal is to center the aircraft in the path by aligning a nosepoint symbol with a target symbol that travels through the path. The tracking highway-in-the-sky is imposed on a standard HUD symbology with pitch ladder, altitude, airspeed, and heading indi-

cators. Whereas the tracking pathway-in-the-sky is a 3-D representation, the tracking task itself can be reduced perceptually to two-dimensional pursuit tracking.

The system monitoring subtask (monitoring) is a configuration of five lights (two green lights normally on, two red lights normally off, and one yellow light normally off) and four graduated sliding gauges with criterion-level indicators. The goal for the pilot is to reset the lights or gauges whenever they deviate from normal status by depressing response buttons on the instrument panel. The target identification subtask (targeting) requires the pilot to scan the textured surface for 3-D targets (spheres, cubes, or pyramids). On detecting a target, pilots activate a screen menu, cycle through menu options, and select the menu item that corresponds to the target shape by depressing switches on the flightstick. Once the appropriate menu item is selected, the task is completed by pulling a trigger mounted on the flightstick.

Dependent Measures

Tracking performance was quantified as the distance from the pilot's nosepoint symbol to the target symbol, calculated as a root mean square (RMS) error, sampled every second. Monitoring performance was quantified in terms of response time, in seconds, to each light or gauge deviation. Targeting performance is quantified as response time, calculated as elapsed time, in seconds, between target presentation and the trigger pull.

Experimental Conditions

Previous research employing the STARFIRE platform indicated that tracking error increased during the initial presentation of a surface target (Scallen, 1997). In the study reported here, consistent with the goals and objectives of AFA (Morrison & Gluckman, 1994), AFA was implemented for the tracking task as a countermeasure to the expected increases in tracking error during these periods. On initial presentation of a target, tracking control was automated for a 20-sec episode, after which, control was returned to the pilot. Three AFA strategies were employed. In full AFA (auto), the tracking task was completely automated during AFA episodes. In one part-task AFA condition, only the vertical component of tracking was automated during AFA episodes while the pilot continued to track horizontally (auto-v). In a second part-task AFA condition, only the horizontal component was automated during AFA episodes while the pilot continued to track vertically (auto-h). During the AFA episode, pilots were cued to the shift in control by an additional display. Monitoring and targeting were completely manual at all times.

The STARFIRE platform was also configured so that either all tasks function independently or the monitoring and tracking tasks were linked. In the independent configuration, the level of performance on any individual subtasks does not effect any of the other subtasks. In the linked configuration, performance on the monitoring subtask can effect the sensitivity of the tracking. If the pilot fails to respond to a monitoring deviation, the sensitivity of the tracking degrades exponentially. The reduction of tracking sensitivity requires more input force to the flightstick to achieve movement of the ownship nosepoint symbol. Sensitivity of the tracking will continue to degrade until the monitoring deviation is reset. Once the deviation has been reset, the tracking sensitivity is immediately returned to the standard setting.

Experimental Procedure

Instruction, training, and practice were provided for each of the three subtasks individually, as well as for the overall multitask environment. All participants performed the STARFIRE tasks in four 15-min conditions: manual, auto, auto-v, and auto-h. All participants performed the manual condition first. The subsequent three conditions were randomized for each participant. Each 15-min condition contained 14 targets and 24 monitoring deviations. Time of occurrence for monitoring deviations and the tracking pathway was constant across the four conditions. At the end of each condition, participants were required to estimate the total duration of the condition.

Experimental Participants

Twenty-four men, nonpilots ($n = 12$) and pilots ($n = 12$), volunteered to participate. Nonpilots were students at the University of Minnesota and had a mean age of 24.75 years (range 19–31, $SD = 4.55$ years). Pilots had a mean age of 38.17 years (range 30–62, $SD = 8.82$ years) with a mean of 1,601.7 flight hr.

EXPERIMENTAL RESULTS

Although system configuration (independent vs. linked) and participant type (pilot vs. nonpilot) factors were included in all analyses, results for these factors will not be reported here. Neither factor interacted significantly with the adaptive allocation conditions. A complete analysis is presented in Scallen (1997).

Confirmation of Degraded Tracking Performance

Tracking performance in the manual condition was examined to validate the specific epoch of allocation employed in this study. Segments (20-sec long) of tracking

RMS error corresponding to the presentation of a surface targets were summed and averaged. This tracking score was then contrasted with the tracking score for the remaining portions of the manual condition in a mixed model, between–within, 2 (participant type) $\times$ 2 (configuration) $\times$ 2 (window of analysis) analysis of variance (ANOVA). Analyses indicate a significant effect for window of analysis, $F(1, 20) = 7.181, p < .05$, indicating that tracking performance is significantly degraded during initial presentation of a surface target.

Tracking

To examine overall tracking performance, tracking RMS errors were summed and averaged for each condition resulting in a single tracking score for each of the four conditions. Tracking error scores were entered into 2 (subject type) $\times$ 2 (configuration) $\times$ 4 (condition) repeated-measures ANOVA. Analysis of tracking error scores indicate a significant condition effect, $F(3, 60) = 24.629, p < .01$ (see Figure 3), in which the manual condition is associated with significantly more error than each of the AFA conditions.

To examine the direct influence of adaptive allocation on tracking performance, tracking error during adaptive allocation episodes of the auto-v and auto-h conditions
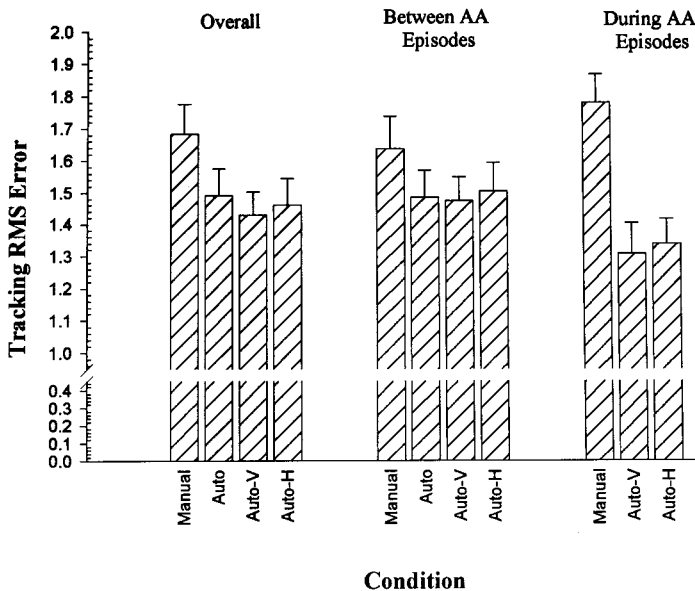

FIGURE 3   Tracking RMS error by condition. Overall tracking performance is displayed as well as tracking performance between AFA episodes and tracking performance during AFA episodes.

were summed and averaged and then compared to tracking error during the corresponding segments of the manual condition in a 2 (subject type) × 2 (configuration) × 3 (condition) repeated-measures ANOVA. Analyses indicate a significant condition effect, $F(2, 40) = 24.065, p < .01$ (see Figure 3), in which the manual condition is associated with significantly more error than each of the part-task AFA conditions.

To examine the indirect influence of adaptive allocation on tracking performance, tracking error outside adaptive allocation episodes of the auto, auto-v, and auto-h conditions were summed and averaged and then compared to the corresponding segments of the manual condition. A 2 (subject type) × 2 (configuration) × 4 (condition) repeated-measures analysis of tracking error indicates a significant condition effect, $F(3, 60) = 9.815, p < .01$ (see Figure 3), in which the manual condition is associated with significantly more error than each of the AFA conditions.

Monitoring

To examine overall monitoring performance, monitoring response times in each condition were summed and averaged, resulting in a single monitoring score for each condition. Repeated-measures analyses indicate a significant effect for condition, $F(3, 60) = 3.410, p < .05$ (see Figure 4), in which manual differs from auto, which itself differs from auto-v.

Targeting

To examine overall targeting performance, response times for targets were calculated and summed and averaged for each condition, resulting in a single target identification score for each condition. Repeated measures analysis of target response
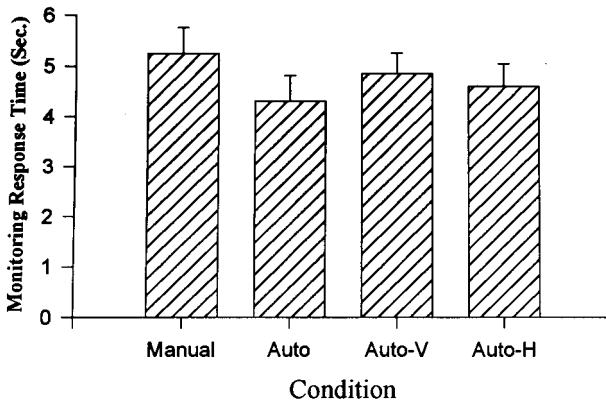

FIGURE 4   Monitoring response times by condition.

times indicate a significant condition effect, $F(3, 60) = 36.097, p < .01$ (see Figure 5), in which all conditions differ from each other.

The number of target responses was deemed large enough to conduct a percentage response analyses (1,130 responses to 1,232 total targets for a response rate of 91.7%). Percentage of target responses (number of targets identified divided by the number of targets presented) was calculated for each condition and analyzed via a repeated-measures ANOVA. Analyses indicate a significant condition effect, $F(3, 60) = 14.775, p < .01$ (see Figure 5). Only auto-v and auto-h conditions do not significantly differ.

Further analyses of targeting performance were conducted on a subset of all target responses. Only correct responses (when the highlighted menu item matched the particular target on the display) were considered for further analyses. Analysis indicates a significant condition effect, $F(3, 60) = 21.681, p < .01$ (see Figure 5). Only auto and auto-h conditions did not significantly differ.

The number of correct target responses was also deemed large enough to conduct a percentage correct response analyses (1,021 correct responses to 1,232 total targets, for a correct target response rate of 82.87%). Percentage of correct target responses (number of targets correctly identified divided by the number of targets presented) was calculated for each condition. Analysis indicates a significant condition effect, $F(3, 60) = 20.158, p < .01$ (see Figure 5). Only manual and auto-h conditions do not significantly differ.

Time Estimation

Time estimations were converted to percentages (estimated time divided by the actual duration of the condition) and entered into repeated-measures analysis. Analyses of time estimation scores indicate a significant condition effect, $F(3, 60) = 4.032, p < .05$ (see Figure 6), in which the manual condition is significantly different from each of the AFA conditions.

DISCUSSION

The purpose of this experiment was to determine the performance effects associated with the implementation of AFA in a multiple-task aviation simulation. This experiment provides support for the implementation of adaptive allocation based on a hybrid model comprising elements of operator performance and mission relevant variables. Implementation of adaptive allocation is an effective countermeasure to the predictable decrease in tracking performance associated with the initial presentation of a surface target. Adaptive allocation also produces benefits for all tasks in the multiple-task battery, even when the automation is not turned on.
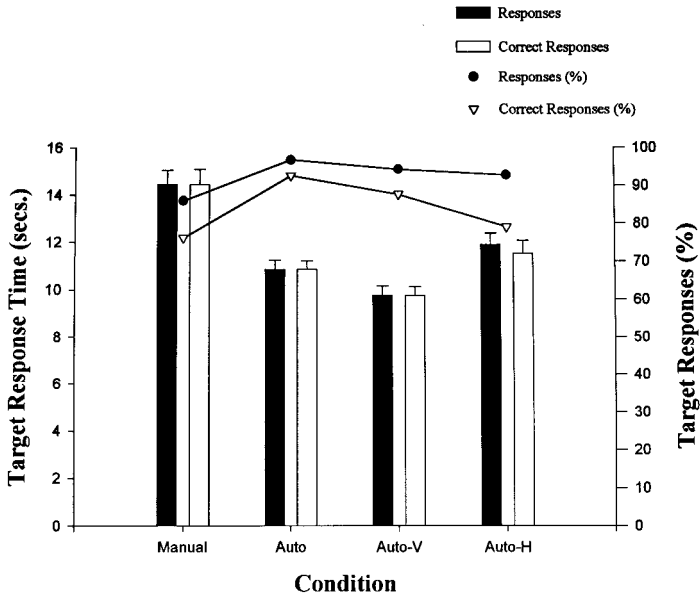
FIGURE 5   Target response times and percentage responses by condition. Data is displayed for total responses and the subset of correct responses. Note that percentage data uses the right *y*-axis.
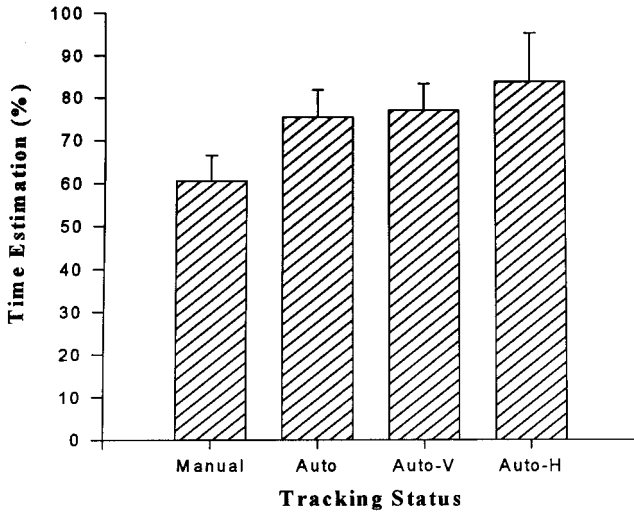

FIGURE 6   Time estimations by conditions. Estimates of duration are converted to percentages of actual duration.

Benefits of Adaptive Allocation

Benefits for adaptive allocation are evident in the tracking task. Pilots demonstrate improved tracking performance for all adaptive allocation conditions. This finding is significant considering that only 31% of the total condition came under the direct influence of adaptive allocation episodes. Effects were strong enough in specific epochs to be reflected in mean measures. Furthermore, the magnitude of the effect was also considerable, as overall means for allocation conditions approximated means for dual task loads for the same experimental tasks (see Scallen, 1997). In effect, overall tracking performance was at the same level as dual task performance despite the fact that participants were in the multitask condition only 69% of the time. How can we account for these data? As predicted, AFA during allocation episodes produced performance benefits. Yet this benefit did not cease once the episode ended. Performance after allocation episodes also approximated demonstrated dual task loads (see Scallen, 1997). This phenomenon is not without precedent. Participants in a study by Parasuraman, Mouloua, and Molloy (1996) continued to demonstrate performance improvements long after the cessation of a single adaptive task allocation episode. Our results, along with those of Parasuraman, Mouloua, and Molloy (1996) and Parasuraman et al. (1994) demonstrate a benefit for adaptive allocation proposed but not experimentally confirmed previously. Adaptive allocation can effectively set up beneficial performance even though it is not actually present. However, a note of caution is warranted. Secondary performance measures, such as tracking variability, may not realize similar benefits (see Scallen, 1997). Future research on the effects of AFA on secondary measures is warranted.

Benefits for adaptive allocation were not restricted to the tracking task, despite the fact that tracking was the only task to come under direct influence of automation. Overall monitoring performance was improved in the full adaptive allocation condition and targeting performance improved in all adaptive allocation conditions. Moreover, different allocation conditions affected targeting in diverse ways, with the auto-v condition demonstrating superior performance. Improvements in monitoring and targeting performance conflict with results of existing studies in adaptive allocation (Parasuraman, Mouloua, & Molloy, 1996; Parasuraman et al., 1994), in which beneficial effects of adaptive allocation were isolated to the task directly under automation influence. In contrast, Scallen et al. (1995) argued that AFA results in microeffects (within task benefits of AFA) and macroeffects (between task benefits of AFA). This distinction may become more important as adaptive allocation research continues and emphasis is placed less at the individual task level and more at a system-wide level. Salvendy (1987) noted that the past half century has seen the effective application of techniques that subdivide activities to improve operations. The next decades will see a sharp emphasis on the study of total systems to optimize operations through the integration of subsystems or parallel systems.

Another benefit produced by adaptive allocation in this way was improved time estimates. Time estimation has not been generally recorded (although see Fortin &

Rousseau, 1987; Guay & Salmoni, 1988; Hancock, Rodenburg, Matthews, & Vercruyssen, 1988; Mihaly, Hancock, Vercruyssen, & Rahimi, 1988; Mitchell & Davis, 1987; Rammsayer & Lustnauer, 1989). However, time estimation benefits have important implications for situation awareness, as well as "the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" (Endsley, 1988, p. 97). Both proponents (Endsley, 1995b) and detractors (Flach, 1995) of situation awareness acknowledge the operator as an adapting agent. Smith and Hancock (1995) discussed how adaptation requires both knowledge and action (see also Neisser, 1976). In contrast to traditional automation, AFA provides both the status of the system (knowledge) and observer participation (action). A consequence of this increased knowledge and participation in this study was more accurate perception of the passage of time. Endsley (1995b) described how acquiring and maintaining SA becomes increasingly difficult as the complexity and dynamics of the environment increase. The manual control conditions of this study replicated this distortion of time perception. It is important to note that we demonstrated that adaptive allocation could mediate the extent of that time distortion. Unfortunately, it is unlikely that situation awareness research will examine this hypothesis in the near future. Current situation awareness measurement techniques do not measure time perception per se, despite claims that advanced levels of situation awareness produce better prediction of events—a highly temporal-related supposition (see Endsley, 1995a).

Finally, a major finding of this experiment is the benefits demonstrated for part-task conditions. Tracking, monitoring, targeting, and time estimation benefitted under the part-task allocation conditions. This is a significant finding in light of the fact that these conditions required participants to provide continuous tracking input even during allocation episodes. Effects for part-task allocation conditions were equivalent to the full-allocation condition and, yet, a complete shift in tracking control was not necessary to achieve comparable performance benefits. The part-task adaptive allocation implemented in this experiment would serve as an excellent alternative to the peripheralization of the flight crew by keeping the pilots in the loop. Performance benefits could be achieved but not at the expense of manual skill. Maintaining observer participation in the system also has other benefits. Wickens (1984) suggested that people need to interact with the system to maintain an accurate perception of the state of the system. Interaction with the system serves to update their system representation. However, the implementation of adaptive automation may not necessarily provide a simple solution to the problems created by keeping pilots out of the loop. Curry (1985, as cited in Wiener, 1989) noted that current flight crews are generally trained to make full use of automation, but they are not trained to make partial use, or revert to more manual modes, when they feel the need. Hopefully, this will change. As long as pilots continue to bear ultimate responsibility for safety

of flight, the human operator must be in command, regardless of the amount or type of automation (Billings & Woods, 1994).

Costs of Adaptive Allocation

Possible costs associated with adaptive allocation can also be identified; specifically, for the vertical allocation condition. Inspection of tracking error scores for the vertical condition indicate large variability. Conversely, this condition produced superior target response times. It appears that participants had to trade off performance on one task to achieve better performance on another. Future research needs to examine how performance trade-offs may hinder the effective implementation of adaptive strategies.

Previously, time estimation results were presented as an adaptive allocation benefit. It is also possible to view these results as indicative of costs. Distortions of time in difficult or complex conditions can be viewed as natural adaptation to safety. The tendency to underestimate time has an established history in surface transportation (see Caird & Hancock, 1994; Knowles & Carel, 1958; Manser & Hancock, 1996; Schiff & Oldak, 1990). The traditional argument in surface transportation has been to view the time distortion as an error on the side of safety. To think another vehicle will hit your car sooner than it actually will provides a margin of safety in which to avoid an accident (i.e., time distortion increases the safety buffer). The time estimation effects in our research can be interpreted to imply a reduction in the safety buffer as perceived time aligned with actual time. However, this argument should be accepted with caution as it seems paradoxical that we would consider an inaccurate perceptual system could be considered to be more safe than an accurate perceptual system (Hancock & Manser, 1998).

Adaptive Allocation: Implications for Design

What, specifically, could adaptive allocation do in complex systems? Lind (1989) suggested that adaptive aiding could help prioritize functions. Funk and Lind (1992) described a pilot-vehicle interface that increased pilot control timing due to the interface's central role of ensuring that the pilot started and completed tasks on time. Other research demonstrated that timing functions may also be appropriate for adaptive allocation. Glenn, Wherry, Cohen, and Carmody (1993) differentiated high resource loads during different phases of a flight mission. Wilson (1993) demonstrated that psychophysiologic workload reached peak levels at different phases of a flight mission for different crew members. Lind and Burge (1993) identified the *within-visual range* portion of air-to-air combat as being particularly time stressed—requiring air crew to process information, make correct decisions, and complete appropriate responses with extreme rapidity. In this time-stress phase, pilots restrict their sampling of information to what they perceive as most important, but they are not always accurate (see Wickens & Flach, 1988). Sirevaag et al. (1993)

reported a study in which pilots had difficulty adhering to the nap-of-the-earth altitude criterion with high communication demands. Rodgers and Holding (1991) reported a study in which performance trends were examined over the course of the day. Dual-task efficiency fell in morning testing sessions but was followed by a recovery later in the day. Andre, Heers, and Cashion (1995) demonstrated that workload preview fostered efficient scheduling when transitioning from low-workload phases to high-workload phases of flight. Finally, O'Hare (1990) conducted a study of pilots' perception of risks and hazards in general aviation and concluded that pilots consistently underestimated the contributory role of pilot factors in accident causation, underestimated the potential for accidents in cruise phases of flight, and greatly underestimated the overall risks of general aviation. In summary, we suggest that AFA could produce positive benefits to a wider range of pilot functions than examined in this study, including task prioritization, mission segmenting, task initiation and cessation, risk identification, and workload management.

Adaptive Allocation: Implications for Philosophy and Theory

Potter (1995) was critical of organizations like the Federal Aviation Administration because they have been unable to take a clear position in respect to cockpit automation. Potter claimed that what is needed is a unifying cockpit automation philosophy—one that is universally accepted and faithfully applied in every activity of every aviation stakeholder. This goal may be overstated, but it does symbolize a growing trend toward theory development in automation systems (see Parasuraman & Mouloua, 1996). Notably, the theory of allocation is often separated from the practice of allocation, with Mital, Motorwala, Kulkarni, Sinclair, and Siemieniuch (1994a, 1994b) being the exception to the rule.

Traditionally, automation is viewed as an "all or nothing" process: Automation is either on or off. The introduction of artificial intelligence transformed our thinking of automation to include grades or levels of automation in which, unfortunately, levels are most often defined by the distance that automation removes the pilot from direct control. However, adaptive allocation is not defined by peripheralized levels because, fundamentally, the operator is always in control. It forces us to rethink the science of automation. The repercussions are numerous. De Greene (1990) noted that human factors research and application may be severely impaired through continued adherence to an obsolete paradigm. The predominant automation paradigm has automation and control entwined in a mutually exclusive relation. By definition, increases in automation mean losses in control, but adaptive allocation is complementary—not exclusionary. The research presented here demonstrates that task partitioning is an effective strategy for adaptive allocation. It is important to note that adaptive allocation also sets up improvements in future performance. For the first time, we have the potential to achieve what Licklider (1960) called *symbiosis*, the coupling between the hu-

man and the system in partnership. Only when this happens can we ultimately achieve the "sharing" and "cooperation" that so many advanced technologies, particularly aiding technologies, claim to be based on.

One philosophical ramification of adaptive allocation involves how we think about human error. Designers have spent decades removing humans from control under the guise of error reduction, although often simply replacing human error with design error (see Bainbridge, 1983). Adaptive allocation will allow humans to interact with systems in new ways—possibly resulting in new kinds of errors. To plan for effective adaptive allocation will require the development of new catalogues of human and machine error, as well as the development of new criteria of human performance for functions that humans may not have a history of performing (e.g., see Fraser, Smith, & Smith, 1992). Furthermore, if humans will be doing new things, we may also need to think about describing, defining, and analyzing tasks in new ways. At what level will we evaluate a task? Taber and Alliger (1995) demonstrated that task-level measurement assesses different psychological processes than those assessed by traditional global and facet measures. We must know more about new human tasks before we begin to evaluate them.

Designers may also need to reevaluate their concepts of human envelopes. Typically, designers understand concepts of machine envelopes (e.g., the maximum and minimum stresses on aircraft airframes during flight). Understanding human envelopes has been routinely restricted to physiological and environmental factors because these, like airframes, are easily observable and measurable. However, how do we expand pilots' attentional envelopes? Hamilton (1993) affirmed that expanding the pilot's envelope allows fuller exploitation of the airframe's envelope and the avionics capabilities. Notice the shift toward human-centered philosophy here. We move from the exploitation of the pilot to the exploitation of the interface.

Finally, it would be a mistake to consider automation as environment specific. Automation is not just pervasive—it is an alliance. Wiener (1985) and Hancock (1996) claimed the cockpit and the office of the future are examples of what biologists call *convergent evolution* whereby disparate systems begin to resemble each other over time because these systems are attempting to solve the same fundamental problem using roughly the same resources. Therefore, if we implement adaptive automation in seemingly disparate environments, it is likely that both the physical environment and the human–machine interaction will coevolve. Inquiry in the area of automation will need to adopt a more interdisciplinary approach if it hopes to evolve. Only then will the notion of adaptive allocation be evolutionary and not revolutionary.

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