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What to Automate: Addressing the Multidimensionality of Cognitive Resources Through System Design

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The implementation of automation relies on the assumption that automation will reduce the operator's cognitive demand and improve performance. However, accepted models demonstrate the multidimensionality of cognitive resources, suggesting that automation must support an appropriate resource dimension to have an appreciable effect. To evaluate this theory, the present study examined the impact of various types of automation on an unmanned ground vehicle (UGV) operator's performance, workload, and stress. The use of a visually demanding task allowed for comparison between an auditory alert (supporting the heavily burdened visual dimension) and a driving aid (supporting action execution, a relatively unburdened cognitive dimension). Static and adaptive (fluctuating based on task demand) levels were implemented for each automation type. Those receiving auditory alerts exhibited better performance and reduced Worry, but also increased Temporal Demand and Effort relative to those receiving driving automation. Adaptive automation reduced workload for those receiving the auditory alerts, and increased workload for those receiving the driving automation. The results from this research demonstrate the need to consider the multidimensionality of the operator's cognitive resources when implementing automation into a system. System designers should consider the type of automation necessary to support the specific cognitive resources burdened by the task.

Keywords: adaptive automation, automation, human automation interaction, human system integration, information processing, level of automation, teleoperation, workload, type of automation, stress

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INTRODUCTION

As technology continues its persistent march forward, humans are increasingly responsible for interacting with complex, multitasking systems. Human operators responsible for air traffic control, nuclear power plant operation, medical practices, aviation, unmanned system operation, and many other fields are dealing with an ever-increasing level of complexity in their systems (Reinerman-Jones, Matthews, Langheim, & Warm, 2011). The operators of these complex systems are often responsible for multiple concurrent tasks. Despite improving efficiency, these complex systems increase task demands and risk pushing the operators' cognitive faculties to or beyond their limits (Cummings & Guerlain, 2007). If workload exceeds a person's resources in a complex system, then often the solution is to redesign the system in such a way that offloads tasking responsibility. Automation is often a solution for mitigating excessive workload and has the potential to support successful system performance while also alleviating the demand on the human operator's cognitive resources.

An example of a workload mitigation system occurs in a nuclear power plant, where operators monitor numerous gauges but the system automatically actuates an alarm when certain events in the plant occur. At that point, the gauges are then used by the operators to understand the state of the plant and return the plant to normal operation. This illustration provides a relatively simple sharing of responsibilities between the human and system. However, not all environments enable clean automation solutions, for instance, using sound for alerts in noisy environments, such as cockpits, or where silence is required for covert operations. In the first situation, the sound is likely to go unobserved, and in the latter, safety and mission success is jeopardized. These and other complex tasking environments convey the need for careful consideration of the users of the automation and their operational context. In other words, system designers should evaluate the cognitive requirements of the specific task environment in order to develop the most effective automation, thus impacting operator state (Kirlik, 1993). In contrast to much of the current research on automation that is concerned with how, when, and why to automate, in the present experiment, we seek to investigate what to automate. Understanding what is automated, or types of automation, would be valuable for system designers.

Automation

Automation, as defined by Parasuraman and Riley (1997, p. 231), is "the execution by a machine agent (usually a computer) of a function that was previously carried out by a human." Automation is capable of providing accuracy and speed advantages that a human could not achieve alone. However, research has repeatedly shown that the use of automation can result in unexpected negative outcomes, including a loss of efficiency, performance, and safety (Parasuraman, 1987; Parasuraman & Riley, 1997; Sheridan, 1997). These limitations are typically a result of traditional implementation of automation in which system designers determine the type and level of automation at fixed, static levels. The automation type is the component of human information processing supported by the automation (e.g., sensory processing, decision making), whereas the level of automation designates the division of control between the human and the automation, with a higher level indicating greater automated control (Parasuraman, Sheridan, & Wickens, 2000). Some systems, such as an autopilot in an aircraft, allow the operator to adjust the level of automation at any time, providing *adaptable* automation (Opperman, 1994; Scerbo, 2001). *Adaptive* automation takes the adaptable concept a step farther by having the system automatically manipulate the level of automation to meet the operator's needs (Hancock & Chignell, 1987).

One goal of adaptive automation is to avoid the problems that commonly result from the implementation of a static level of automation (misuse, disuse, skill degradation, etc.; Parasuraman & Riley, 1997; Sheridan, 1997) while still reaping its benefits. As the term suggests, adaptive automation allows the automated aid to be adjusted responsively to better meet the needs of the human operator (Rouse, 1988). Through this method, the system maintains a lower level of automation during periods of routine performance, allowing the operator to preserve control without risking a reduction in overall system performance. However, when there is an increase in demand on the human operator, the system will respond by increasing the level of automation. The purpose for this adaptation is to offload some of the demands required for task performance, freeing the operator's cognitive resources to focus on critical task elements. For the system to be capable of adapting the level of automation to optimally support the operator's needs, system designers must adopt a theory of cognitive processing that allows them to maintain an accurate representation of the operator's mental state (Byrne & Parasuraman, 1996). This is a critically important component of adaptive systems, as altering the level of automation risks temporarily reducing the operator's performance (Reinerman-Jones, Taylor, Sprouse, Barber, & Hudson, 2011). Therefore, the system must maintain an accurate representation of the operator's cognitive state to ensure that changes to the level of automation occur only at appropriate times.

The Multidimensionality of Cognitive Resources

Authors of early investigations into cognitive processing considered mental resources to be a single pool of energetic capacities (Kahneman, 1973). However, thorough evidence now exists supporting multiple resource capacities (Wickens, 1980, 1984), metaphorically dividing cognitive resources into separate, distinct pools. Results of dual-task studies indicate that for specific types of tasks, little to no detriment was caused by the introduction of a concurrent secondary task. For example, Wickens (1976) reported that the performance of physical action execution was met with a degradation in the performance of a simultaneous manual tracking task, indicating that both tasks rely on similar cognitive resources, whereas the performance of a visual signal detection task caused no such degradation on the same manual tracking task. These results, and many others (e.g., Isreal, Chesney, Wickens, & Donchin, 1980; Kantowitz & Knight, 1976), support the multiple resource perspective that separate, unique pools of cognitive resources are responsible for the performance of various cognitive functions (see Wickens, 2008, for further review).

Despite the evidence in favor of multiple resources, designers of adaptive systems continue to consider operator workload as a unidimensional construct, advertently or inadvertently, generally describing workload as "high" or "low" without recognition of the underlying multidimensionality. This discordance between accepted theory and current practice demonstrates a clear need for system designers to reconsider their approach when implementing adaptive automation. Previous research provides support for the need to appropriately match the type of automation to the cognitive dimension utilized to perform the task. For example, the use of automation that supports the execution of physical actions (such as driving automation) has been shown to provide little benefit for the performance of a visual target identification task (Cosenzo, Chen, Reinerman-Jones, Barnes, & Nicholson, 2010). In contrast, performance on a target identification task did improve from automation that supported the operator's perceptual resources (Tannen et al., 2000). Griffiths and Gillespie (2005) found similar results, with action execution automation providing little benefit for the performance of an auditory perception task, though it did improve the performance of a driving task. This evidence shows that a single form of automation can be beneficial when implemented appropriately in support of a task relying on similar cognitive resources but has little effect when used to support tasks requiring different cognitive resources.

Purpose for the Current Study

Researchers investigating the effects of automation on operator performance, stress, and workload have tended to focus on the level of automation and the invocation methods used to alter it (Szalma & Taylor, 2011; Wickens, Li, Santamaria, Sebok, & Sarter, 2010), but little attention has been paid to the type of automation employed. Kirlik (1993) provided an insightful discussion of the importance of providing automation that is appropriate for the operational context, and yet little empirical research has been conducted to evaluate this concept. The limited research that has involved evaluating the impact of varying types of automation has done so only on the basis of the stage of information processing supported by the automation. This work adopts simplified models of the human information-processing loop, typically limited to four stages: information acquisition, information analysis, decision making, and action execution. There is evidence that operators receive the greatest benefit from adaptive automation applied to the information acquisition or action implementation stages of the cognitive process, and it has been argued that these effects are consistent across task types (Kaber, Perry, Segall, McClernon, & Prinzel, 2006; Kaber, Wright, Prinzel, & Clamann, 2005).

However, with this generalized interpretation, one overlooks the possibility that these types of automation may provide the greatest benefit only when operators experience greater demands within the sensory processing and action implementation stages of information processing. This alternative explanation would suggest that no single type of automation could consistently provide the greatest benefit across all task environments. Rather, the type of automation that best supports a task varies on the basis of the degree to which the task requires the use of particular cognitive resources.

To investigate this theory, the goal for the present study was to advance the scientific understanding of the interaction between human operators and adaptive automation systems by manipulating the type and level of automation in the context of changing levels of task demand. The use of multiple simultaneous tasks in a simulated unmanned robot control system environment ensured that participants experienced demand across multiple cognitive dimensions (Rouse, 1977) within a task that accurately reflected the type of complex task environment experienced by current and future Warfighters. More than 6,000 unmanned vehicles have been deployed in military operations in Iraq and Afghanistan (Pitts, 2009), and their numbers are expected to grow exponentially in the near future (U.S. Army UAS Center of Excellence, 2010). Therefore, unmanned vehicle control was selected as being the area capable of receiving the greatest benefit from this evaluation.

Focusing task demand within one specific cognitive dimension allowed for a comparison between a type of automation supporting that mental dimension (automation matched to demand type) with one that did not (automation mismatched to demand type). Wickens' (2008) 4-D multiple resource model was used to classify task demands and forms of automation according to the cognitive dimension they impacted. This model describes cognitive resources along four separate dimensions. The *stages of processing* dimension differentiates between perceptual/cognitive processes and the execution of actions. The *codes of processing* dimension offers a distinction between spatial and verbal processing. The *modalities* dimension is relevant only within the perceptual/cognitive stage of processing and differentiates between visual and auditory perception. Nested within the visual perception modality is the *visual channels* dimension, which distinguishes between focal and ambient vision. A single task, or form of automation, can be defined within multiple cognitive dimensions. For example, a task can rely on the perceptual stage, in the spatial code, using the visual modality with the focal visual channel.

Automation that supports the cognitive dimension under greatest demand from the task was hypothesized to improve operator performance, workload, and stress relative to automation that supported an alternate cognitive dimension. Additionally, the benefit of adaptively adjusting the level of each type of automation to match the level of task demand (adaptive automation) as opposed to maintaining a consistently high level of automation (static automation) was investigated. Adapting the level of automation to meet the level of demand was hypothesized to improve performance, workload, and stress only when the type of automation was appropriately matched to the type of demand imposed by the task. When using a type of automation mismatched to the task demands, adaptively altering its level was predicted to not provide any benefit or to be detrimental.

METHOD

Sample Population

Data were collected from 60 university undergraduates, 31 females (age: M = 19.31, SD = 2.19) and 29 males (age: M = 19.78, SD = 3.47). Thirty-one participants received the automation matched to demand type (an auditory alert), and 29 participants received automation mismatched to demand type (a driving aid).

Experimental Task

The experimental task simulated the operation of an unmanned ground vehicle (UGV) from a remote operator control station, utilizing the Mixed Initiate Experimental (MIX) test bed (Figure 1; Barber et al., 2008; Reinerman-Jones, Barber, Lackey, & Nicholson, 2010). The mission took place in a generic Middle Eastern town based on a terrain database of the Military Operations in Urban Terrain (MOUT) site in Twentynine Palms, California. Participants completed the task on a standard desktop computer with a 22-in. monitor (16:10 aspect ratio) with a joystick and mouse. The participant was responsible for completing three separate tasks simultaneously: driving the vehicle along a prespecified path, monitoring a video feed for enemy threats, and monitoring a map display for changes in entity locations.

Driving task. The driving task was designed to require a low level of cognitive resources from the action execution dimension. The participants' task was to follow a predefined path presented to them in the route map window. The window displayed an icon representing the UGV's current location and heading in the center with north always at the top of the screen. Participants controlled the movement of the UGV using a joystick along four unique routes. All routes had an equal number of turns (eight in each) with an equal number being left and right. Each route required 24 min to complete.

Threat detection task. The threat detection task was designed to require a moderate level of cognitive resources from the focal visual perception dimension. As the vehicle drove along the route, the participant monitored a video feed from the perspective of the front of the UGV in the threat

Figure 1. The Mixed Initiate Experimental test bed with outlines overlaid to differentiate task areas.

Figure 2. Examples of characters displayed throughout the environment. From left to right: friendly soldier, friendly civilian, enemy soldier, insurgent.

detection window. Various stationary objects, such as buildings, trees, vehicles, and people, populated the environment. The participant's task was to monitor the people along the route for potential threats. Four categories of people were present in the environment (Figure 2): friendly soldiers, friendly civilians, enemy soldiers, and insurgents (armed civilians). The participant responded to an enemy soldier or insurgent by clicking on the threat in the window using the mouse.

Participants viewed the human characters at an average rate of 24 nonthreats and 2 threats each minute, resulting in a signal-to-noise (threat-to-nonthreat) ratio of 1:12, with additional neutral objects (e.g., rubble piles, vehicles, and trees) presented at an average rate of 15 per minute.

Change detection task. The change detection task was designed to require a fluctuating level of cognitive resources (see Manipulations section, next) from the focal visual perception dimension. This task simulated an intelligence monitoring assignment, representative of the type of perceptual task commonly required in military command-and-control operations (Tollner, 2007). A separate map at the bottom of the screen used representative icons to display the current location of various entities. Although these icons do convey information regarding entity type and affiliation through military convention (Department of Defense, 2005), the participant was not trained or instructed to attend to these details. The participant's task was only to monitor the presence and location of the icons and respond when one of three types of changes occurred: "appear" (a new icon was added to the display), "disappear" (an icon was removed from the display), or "movement" (an icon changed location). After recognizing one of these changes, the participant responded by clicking the appropriate button (Appeared, Disappeared, or Movement) above the change detection map.

Manipulations

Type of automation. Participants were randomly assigned to receive one of two types of automation intended to support either an appropriate or

TABLE 1: Details of the Task Demand Manipulation for the Change Detection Task

Variable	Low Demand	High Demand
Event rate (average)	4 changes/minute	10 changes/minute
Signal saliency	3 icons change	1 icon changes
Memory load (average)	8 icons	24 icons

an inappropriate cognitive dimension, based on the specific demands of the experimental task. One group of participants received an auditory alert that supported the visual perception cognitive dimension, the primary cognitive function required by the task, by playing a sound over speakers at the precise moment a change occurred on the change detection map. The auditory alert notified the participant only that a change occurred, providing no indication of the type of change, leaving the responsibility of classifying and responding to each change for the participant. The goal of this alert was to reduce the demand on the operator's visual perception resources, supporting his or her ability to perform the change detection task using only peripheral vision while maintaining primary focus on the threat detection task.

The other group of participants received driving automation that supported the action execution cognitive dimension, a minor component of the task, by driving the UGV along the route automatically. The participant maintained a limited level of supervisory control with a Pause button that stopped the UGV in place until the participant chose to resume.

Task demand. The level of task demand was manipulated at regular intervals, a necessary element to support the implementation of adaptive automation. This manipulation simultaneously altered the parameters of the change detection task in three ways: event rate, signal saliency, and working memory load. Periods of high demand consisted of a faster event rate, decreased signal saliency, and increased memory load relative to periods of low demand. *Event rate* describes the number of changes that occurred over time, consisting of equal numbers of appear, disappear, and movement events. The time delay between change events varied across trials to avoid the events occurring at easily predictable intervals. *Signal saliency* describes the perceptual difficulty of recognizing a change and was manipulated by the number of icons that changed per event, with the same type of change occurring for all icons involved in a single event. Working memory load adjusted the average number of icons present on the map at a single time. The specific details of the manipulations are listed in Table 1.

Static/adaptive automation. Participants of both groups experienced their assigned automation at both low and high levels. At the low level, the automation provided no assistance, meaning the participants drove the vehicle manually using the joystick and received no auditory alerts for the change detection task. At the high level, the automation provided the assistance described previously.

All participants experienced their assigned type of automation in both static and adaptive conditions. A previous series of experiments that utilized static and adaptive automation in addition to manual control indicated that static and adaptive automation yielded significantly better performance and lower workload than manual control (Cosenzo, Chen, Reinerman-Jones, et al., 2010; Cosenzo, Chen, Drexler, et al., 2010; Taylor, Reinerman-Jones, Cosenzo, & Nicholson, 2010). Therefore, the present study focused only on understanding the benefits of solutions for automation type within environments that employ automation. The static condition maintained a consistently high level of automation throughout a single experimental scenario. In the adaptive condition, the level of automation fluctuated as a function of the task demand (see Experimental Scenarios section for details).

Experimental scenarios. Each participant received two static automation and two adaptive automation scenarios, and each scenario

TABLE 2: The Changing Levels of Automation and Task Demand for the Four Experimental Scenarios

Variable		Time (Minutes) 0:00–2:59	3:00–5:59	6:00–8:59	9:00–11:59	12:00–14:59	15:00–17:59	18:00–20:59	21:00–24:00
Scenario 1	Task demand	Low	High	High	Low	Low	High	High	Low
	Level of automation	High	High	High	High	High	High	High	High
Scenario 2	Task demand	High	Low	Low	High	High	Low	Low	High
	Level of automation	High	High	High	High	High	High	High	High
Scenario 3	Task demand	Low	High	High	Low	Low	High	High	Low
	Level of automation	Low	Low	High	High	Low	Low	High	High
Scenario 4	Task demand	High	Low	Low	High	High	Low	Low	High
	Level of automation	High	High	Low	Low	High	High	Low	Low

was 24 min. The order in which these scenarios were presented was counterbalanced across all participants. Two scenarios, one adaptive and one static, began under low task demand, and the remaining two scenarios began under high task demand. Task demand always alternated between low and high at 3, 9, 15, and 21 min. For example, scenarios that started under low demand changed to high demand 3 min into the scenario, moved back to low demand at 9 min, changed to high demand at 15 min, and returned to low demand at 21 min, which continued until the end of the scenario. Scenarios that began under high demand followed an opposite structure.

In the two adaptive automation scenarios, automation began at a level matched to the initial task demand (low automation for low demand, high automation for high demand). The level of automation then adapted to the changing task demand throughout the scenario but with a 3-min delay. For example, if the task demand increased from low to high 3 min into the scenario, the automation maintained a low level until it increased to a high level at 6 min. Task demand then returned to a low level at 9 min, whereas the automation maintained a high level until it decreased at 12 min (Table 2). The reason for this delay was to simulate the time needed for the system to detect a change in the operator's cognitive state. Although 3 min is longer than an adaptive system may require to detect a change in operator workload, the delay was intentionally overestimated. Several studies have shown evidence that adjusting the level of automation while an operator is performing a task can have a brief negative impact on performance, workload, and situation awareness (Hilburn, Molloy, Wong, & Parasuraman, 1993; Kaber, Wright, & Sheik-Nainar, 2006; Parasuraman, Bahri, Molloy, & Singh, 1991; Reinerman-Jones, Taylor, et al., 2011). Given these findings, it appears that the level of automation should not adjust immediately upon detecting a change in operator workload. The introduction of a slight delay before changing the level of automation provides the system with adequate time to ensure that the newly detected state will persist, avoiding the risk of changing the level of automation (temporarily reducing operator performance) to meet a fleeting level of demand.

Additional Measures

Participants completed a demographics questionnaire that measured standard items, such as age and gender, and confirmed they met the inclusion criteria: normal state of health, normal color vision, and no prior military experience.

The Dundee Stress State Questionnaire (DSSQ; Matthews et al., 2002) was used to assess the participants' subjective stress levels. The short form was used (Helton, 2004), which measures secondary factors only (Task Engagement, Distress, and Worry). Participants completed a pretest before beginning the experiment and a posttest following each experimental scenario.

The NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988) measured the participants' subjective workload after each experimental scenario.

An electrocardiogram (ECG) system recorded the participants' heart activity. A Thought Technology ProComp Infiniti encoder with an ECG-Flex/Pro sensor measured the electrical current across the heart at 2048 Hz. The So and Chan method (Tan, Chan, & Choi, 2000) was used to locate heartbeats within the ECG signal. The statistical variance of the interval between heartbeats was used to calculate heart rate variability (HRV), which decreases with increases in workload (Wilson, 1992).

Experimental Procedure

The participant began with the demographics and DSSQ questionnaires followed by a recording of 5 min of resting ECG data to serve as a baseline. The researcher then described the experimental task through a PowerPoint presentation. The participant completed three 2-min practice scenarios to perform each task component individually and two 5-min practice scenarios to perform all of the tasks simultaneously. The participant then began the first full experimental scenario. After completing the scenario, the participant completed the DSSQ and the NASA-TLX. This pattern was repeated for the remaining three scenarios for an entire duration of 2 hr.

RESULTS

Manipulation Check

In the first analysis, we evaluated the task demand and level of automation manipulations to confirm that each had the desired effect on performance. Performance on the change detection task was recorded as the percentage of changes correctly identified (changes to which the participant responded with the correct classification).

We compared average performance on the change detection task across all experimental scenarios during periods of low and high demand using a repeated-measures t test. As expected, a significant effect was found for the percentage of changes correctly identified, $t(59) = 18.328$, $p < .001$, such that performance was significantly better under low demand ($M = 61.97\%$, $SD = 11.63$) than under high demand ($M = 43.86\%$, $SD = 12.74$, $d = 1.48$).

The effect of the level of each type of automation on change detection performance was also evaluated through equivalent repeated-measures t-tests. A significant effect was found for those in the auditory alert condition, $t(30) = 12.356$, $p < .001$, such that performance was significantly better with a high level of automation ($M = 64.03$, $SD = 13.52$) than low level of automation ($M = 43.55$, $SD = 9.93$, $d = 1.75$). A significant effect was also found for those in the driving automation condition, $t(28) = 2.922$, $p = .007$, such that performance was significantly better with a high level of automation ($M = 47.80$, $SD = 9.63$) than with a low level of automation ($M = 44.37$, $SD = 11.18$, $d = 0.33$), although the strength of this effect was much weaker than that found for the auditory alert condition.

The task demand and level of automation manipulations were found to have no significant effect on threat detection performance ($p > .05$ in each case).

Performance

With a series of 2 × 2 mixed-model ANOVAs, we evaluated all dependent variables, with type of automation (driving or auditory alerts, between subjects) and automation adaptability (static or adaptive, within subjects) serving as independent variables.

Change detection performance. Significant main effects were found for the type of automation, $F(1, 58) = 24.720$, $p < .001$, and automation adaptability, $F(1, 58) = 56.398$, $p < .001$. The participants who received the auditory alerts performed significantly better ($M = 55.02\%$, $SD = 10.12$) than those who received the driving automation ($M = 42.03\%$, $SD = 10.12$, $d = 1.28$). Participants also performed significantly better in scenarios with static automation ($M = 51.52\%$, $SD = 11.12$) than with adaptive automation ($M = 45.53\%$, $SD = 10.02$, $d = 0.566$). A significant interaction between automation adaptability and type of automation was also found, $F(1, 58) = 18.551$, $p < .001$. One-way ANOVAs provided further evaluation of this interaction by showing the effect of automation adaptability within each type of automation separately (Figure 3). Within the auditory alert condition, a significant main effect for automation adaptability was found, $F(1, 30) = 85.003$, $p < .001$, with participants performing

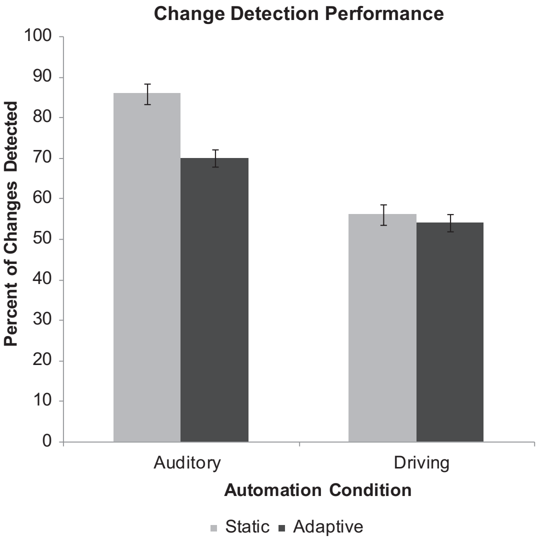

Figure 3. Percentage of changes correctly detected as a function of automation type and adaptability.

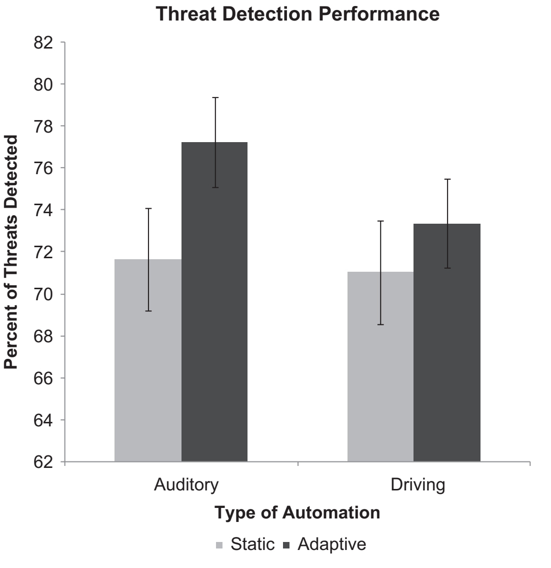

Figure 4. Percentage correct detected when detecting threats as a function of automation type and adaptability.

better in static automation scenarios (M = 59.73%, SD = 11.25) than in adaptive scenarios (M = 50.31%, SD = 10.60, d = 0.862). Within the driving automation condition, the main effect for automation adaptability was significant, $F(1, 28) = 4.275$, $p = .048$. Again, participants performed better in the static automation scenarios (M = 43.31%, SD = 10.96) than in the adaptive scenarios, though this effect was weaker than that found for the participants who experienced the auditory alerts (M = 40.75%, SD = 9.354, d = 0.251). See Appendix A for detailed descriptive statistics.

Threat detection performance. Automation adaptability was found to have a significant effect on the percentage of threats detected, $F(1, 56) = 11.040$, $p = .002$, with performance greater with adaptive automation (M = 75.28%, SD = 13.05) than with static (M = 71.32%, SD = 14.95, d = 0.2825). The main effect for type of automation and the interaction were not statistically significant (Figure 4). See Appendix B for detailed descriptive statistics.

Questionnaires

Subjective stress (DSSQ). The ANOVAs conducted on the DSSQ values from each scenario (with the use of change-from-baseline values to account for individual pretask variation; Figure 5) indicated a significant main effect of type of automation for Worry, $F(1, 58) = 4.465$, $p = .039$. The participants who received the auditory alerts reported significantly lower levels of worry ($M = -2.685$, SD = 5.26) than did those who received the driving automation (M = 0.250, SD = 5.38, d = 0.552). Results did not indicate any other significant main effects or interactions ($p > .05$ in each case). See Appendix C for detailed descriptive statistics.

Subjective workload (NASA-TLX). The NASA-TLX produced six subscales of subjective workload: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration Level (Figure 6). Missing data from one participant in the auditory alert condition reduced the sample for the following analyses. See Appendix D for detailed descriptive statistics.

Temporal demand. A significant main effect of automation type was found for the Temporal Demand subscale, $F(1, 57) = 6.395$, $p = .014$. The participants who received the auditory alerts reported significantly higher levels of temporal demand (M = 64.92, SD = 21.34) than did those who received the driving automation (M = 50.86, SD = 21.34, d = 0.659).

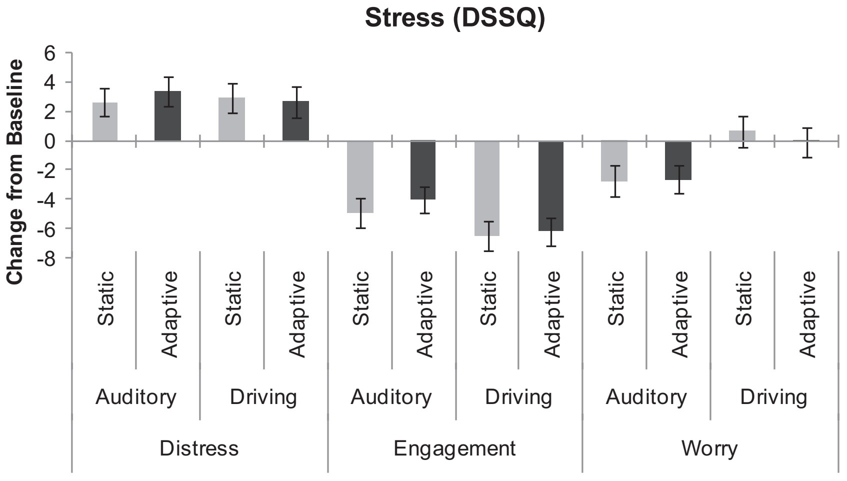

Figure 5. Stress reported from Dundee Stress State Questionnaire responses as a function of type and adaptability of automation. Values reported as change relative to baseline.

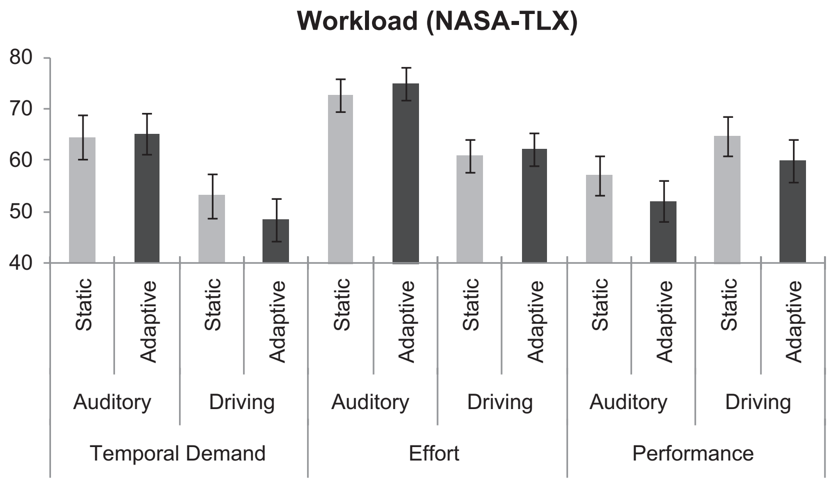

Figure 6. Workload reported from NASA Task Load Index responses as a function of type and adaptability of automation.

Effort. A significant main effect of automation type was found for the Effort subscale, $F(1, 57) = 10.235$, $p = .002$. The participants who received the auditory alerts reported significantly higher levels of effort ($M = 73.96$, $SD = 14.84$) than did those who received the driving automation ($M = 61.60$, $SD = 14.84$, $d = 0.833$).

Performance. A significant main effect was found for automation adaptability on the Performance subscale, $F(1, 57) = 6.721$, $p = .012$. Participants rated this scale higher (indicating that they believed their performance was worse) for scenarios with static automation ($M = 60.95$, $SD = 21.08$) than did those with adaptive automation ($M = 56.08$, $SD = 21.62$, $d = 0.228$).

Frustration, Mental Demand, and Physical Demand. There were no significant main effects or interactions found for the Frustration, Mental Demand, or Physical Demand subscales ($p > .05$ in each case).

HRV

The sample used for these analyses is reduced to 57 (30 auditory alert condition, 27 driving automation condition) due to technical difficulties in physiological data collection. The ANOVAs

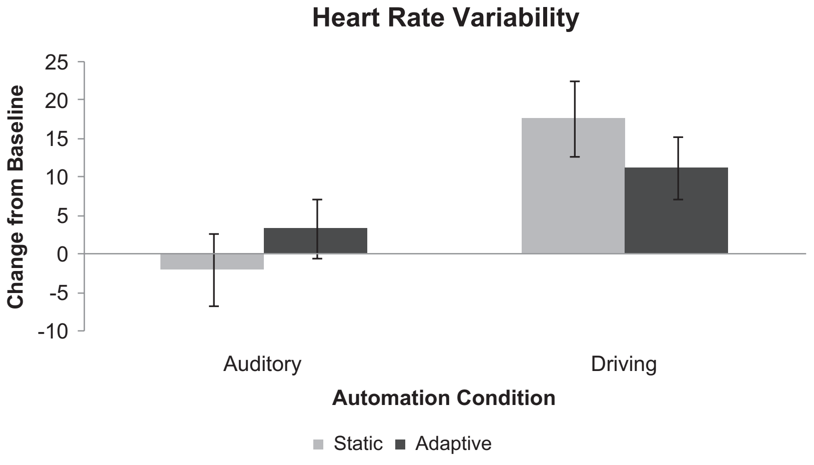

Figure 7. Heart rate variability as a function of adaptability and type of automation. Lower values indicate higher levels of workload.

conducted on the HRV values from each scenario (with the use of change-from-baseline values to account for individual variation) indicated a significant effect of type of automation for HRV, $F(1, 55) = 5.336$, $p = .025$. Those receiving the auditory alerts had lower HRV values, indicating greater workload ($M = 0.610$, $SD = 22.41$), than did those receiving the driving automation ($M = 14.34$, $SD = 22.41$, $d = 0.613$). The interaction between type of automation and adaptability was also significant, $F(1, 55) = 11.518$, $p = .001$. Further analysis revealed that the effect of adaptability on HRV varied as a function of automation type (Figure 7). Those participants who received the auditory alerts, $F(1, 29) = 6.159$, $p = .019$, experienced higher HRV values, indicating lower workload, during adaptive automation scenarios ($M = 3.287$, $SD = 21.72$) than in static scenarios ($M = -2.068$, $SD = 22.31$, $d = 0.243$). This trend was reversed for those who received the driving automation, $F(1, 26) = 5.396$, $p = .028$, who experienced higher HRV values, indicating lower workload, with static automation ($M = 17.519$, $SD = 28.30$) than with adaptive ($M = 11.160$, $SD = 20.51$, $d = 0.257$). See Appendix E for detailed descriptive statistics.

DISCUSSION

In this study, we examined the importance of matching the type of automation to the dimension of cognitive resources most heavily consumed by a task, particularly within adaptive automation systems. Two primary hypotheses were investigated, each of which was supported by empirical evidence through statistical analyses. Specifically, automation designed to match the cognitive demands of a task is more beneficial than automation mismatched to cognitive demands, and adapting the level of automation to meet demand is beneficial only when the automation is matched to the cognitive demands of the task.

Type of Automation

As predicted, the auditory alerts, designed to address the specific demands the operator is subjected to by the task, did improve performance, although this improvement was limited to the change detection task. However, the prediction that a performance improvement would result from the freeing of cognitive resources did not occur. In fact, the auditory alerts were found to significantly increase the subjective Temporal Demand and Effort scales of the NASA-TLX, resulting in a performance–workload dissociation (Yeh & Wickens, 1988). One explanation for this disparate finding is that the task demands could be such that the participants performing them fall on the lower end of the curvilinear relationship between workload and performance, the hypostress region of dynamic instability in Hancock and Warm's (1989) model. Therefore, an increase in workload would elicit a corresponding increase in

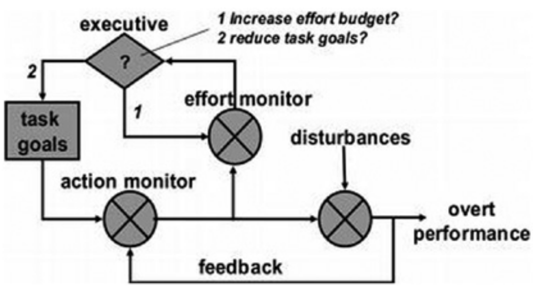

Figure 8. Hockey's (1997) cognitive-energetical model of compensatory effort.

performance. However, given the magnitude of the values reported on the various NASA-TLX subscales, this explanation is unlikely.

Instead, Yeh and Wickens (1988) suggest that performance–workload dissociations are often the result of the investment of greater resources to the performance of a resource-limited task. Therefore, the results are more effectively explained through the cognitive-energetical model (Hockey, Gaillard, & Coles, 1986; Hockey, 1997), which proposes the addition of *compensatory effort* to alternative resource theories. Hockey suggests that an operator's performance on a task relies not only on the level of workload experienced but also on the actions of a higher-level, goal-focused managerial system. This system maintains goals for both performance and cognitive/emotional well-being (i.e., workload and stress) and is capable of making deliberate sacrifices in one area to benefit the other (Figure 8). The decision to adjust the effort devoted to a task is determined by the discrepancy between the current level and goal state for both performance and cognitive energy. The use of the auditory alerts influences this decision by making each signal more salient, allowing the operator to easily recognize missed signals. Increasing awareness of missed signals will inherently cause a corresponding decrease in perceived performance. Decreasing the operator's perceived level of performance causes an increased discrepancy from the performance goal state, motivating him or her to sacrifice additional cognitive energy to elevate perceived performance closer to the goal state.

The one effect of the automation manipulation not directly explained by the cognitive-energetical model is that those who received the auditory alerts reported significantly lower levels of the worry dimension of stress than those who received the driving automation. Worry is representative of the cognitive processes of stress (including self-focus, self-esteem, task-related cognitive interference, and task-irrelevant cognitive interference) and declines over time in the performance of most tasks. This decline is typically most prevalent in the self-focus and task-irrelevant cognitive interference facets since focus shifts away from the self and is devoted to the task (Matthews et al., 1999). This pattern is consistent across many types of tasks, including reading, card sorting, and working memory tasks (Matthews et al., 2002), and is evident in the participants who received the auditory alerts. However, the level of worry reported from those receiving the driving automation remained unchanged from baseline values, a trend typically found only from the performance of visual vigilance tasks. Similarly, HRV increased relative to baseline as a result of driving automation.

An initial interpretation of this finding is that the increase in HRV is simply a result of the vascular needs from physical exertion required to operate the joystick. However, this exertion is minimal and would be greatest at the beginning and end of the driving condition, thus one could expect HRV to be greatest during these times. This is not the case and in fact, increased HRV relative to baseline is persistent throughout the scenario. Therefore, the increase in HRV (relative to baseline recordings) caused by the driving automation provides further evidence that the participants in this condition were disengaged from the task and were experiencing a vigilance response (Chua et al., 2012). Therefore, the results suggest that the implementation of driving automation changed the structure of the task to rely primarily on sustained attention even though other hallmarks of vigilance performance, such as reduced sensitivity over time, were not evident (Matthews et al., 2010). This change in task structure may result from the fact that the driving task is the only continuous-control portion of the experimental scenarios. Therefore, offloading this task from the operator through automation leaves only the threat detection and change detection tasks to perform, both of which rely on signal detection processes. Sheridan (1992) specifically discusses this issue as a potential pitfall of the use of automation in the realm of robot control tasks, and these findings offer further support for his claims.

Adaptive Automation

The adaptive automation manipulation had consistent effects on performance across both automation types. For both conditions, adaptive levels of automation resulted in better performance on the threat detection task and poorer performance on the change detection task. Given this consistency, the HRV data provided the most compelling support for the hypotheses related to adaptive automation. Adaptively altering the level of automation reduced the level of workload for those in the auditory alert condition but caused an increase in workload for those in the driving automation condition. This effect of the automation manipulation provides considerable support for the primary hypothesis that matching the type of automation to the type of demand experienced is critical, particularly within an adaptive environment. As expected, adapting the level of the auditory alert automation to meet task demands reduced operator workload because the automation directly supported the cognitive resources that were impacted by the fluctuating task demand. However, the driving automation supported cognitive resources unaffected by the task demand manipulation, and pairing the level of automation to the level of demand did nothing to support the operator's needs and served only as a distraction, causing an increase in workload (Reinerman-Jones, Taylor, et al., 2011).

CONCLUSIONS

The use of the driving automation, unmatched to the type of demand subjected by the task, provided relatively little benefit to the operator. In fact, the driving automation showed evidence of disengaging the operator. On the other hand, the use of the auditory alerts, designed to support the cognitive faculties under the greatest demand, significantly improved mission performance. Further, operator workload declined when the level of auditory alert automation varied adaptively on the basis of the level of demand imposed by the task, but workload actually increased when the level of driving automation adapted to the level of demand.

However, the use of the auditory alerts was still not ideal. The intention was to have the alert offload some of the perceptual demands of the task by increasing the saliency of the perceptual events. This method proved to be effective, resulting in improved change detection performance, but also caused a simultaneous increase in subjective workload (effort and temporal demand, specifically). The auditory alerts appeared to improve operator performance primarily by motivating the operator to sacrifice additional cognitive energy by increasing awareness of performance errors. Ultimately successful in its primary goal of improving performance, this associated cost in operator cognitive resources is an important factor to consider before implementing such an aid in any system.

The theoretical implications of this study demonstrate that the type of automation implemented within an environment has a considerable impact on the operator in terms of performance as well as cognitive/emotional state. These results contradict previous theories proposing that humans are best supported by automation of the information acquisition or action implementation phases of information processing (Kaber et al., 2005). It appears that such a generalized statement is not true across all task types, but rather, the type of automation that best supports the operator is that which supports the cognitive dimension most burdened by his or her task. Providing automation that does not support the appropriate cognitive dimension can result in many potential problems (disengagement, skill degradation, etc.) without achieving any benefit.

This study provides further support for the multidimensionality of cognitive resources and demonstrates the importance of considering these dimensions when implementing automation. In this study, we evaluated automation within a military UGV control setting; however, the findings are not expected to be limited to the operation of unmanned vehicles or even military tasks. Any complex task environment in which the operator may experience more than one type of demand would benefit from matching automation type to the demand type currently experienced by the operator. In fact, designers of even relatively simple tasks in which only a single form of demand is present must also consider whether the automated assistance provided to the operator truly supports the demand imposed by the task. Task analyses can provide valuable insight for system designers to better understand the cognitive demands of the component tasks within their system, identifying the cognitive dimension that will be best served by automation support. Serious consideration must be given to the implementation of automation if any benefit is to come of it. Failure to do so risks employing automation that provides little to no operational advantage or, worse, that actually impairs the operator's ability to perform their task.

Future Research

The current study provides preliminary support for the importance of matching automation type to the type of demand experienced by the operator, but additional research is necessary to ensure that this effect is consistent for all types of demand. The task used in the current study focused only on imposing (and alleviating) perceptual demands. Therefore, further evaluation is necessary to investigate the same concept under varying levels of other types of demand, such as decision making or action implementation. Along those lines, investigating operator strategies for performing one task, like driving, and coping with demands imposed by other tasks, such as change detection and threat detection, would more clearly inform system designers about the impact of types of automation.

In addition, before a complex system can become truly adaptive to various types of demand, researchers must develop real-time metrics that are more diagnostic of specific types of cognitive demand. Most metrics of cognitive state derived from physiological measures classify workload along a single continuum. These measures must evolve dramatically to become capable of discriminating between various types of mental demand before a system can be capable of truly understanding the operator's cognitive state on a multidimensional level in real time, a necessary capability before the system can adapt to meet the operator's specific needs.

APPENDIX A

Descriptive Statistics: Change Detection Performance

Measure	Condition	Adaptability	*n*	Mean	Standard Error
Percentage	Auditory	Static	31	59.732	1.995
of changes		Adaptive	31	50.312	1.799
correctly	Driving	Static	29	43.305	2.063
identified		Adaptive	29	40.752	1.860

APPENDIX B

Descriptive Statistics: Threat Detection Performance

Measure	Condition	Adaptability	*n*	Mean	Standard Error
Percentage	Auditory	Static	31	71.627	2.454
of threats		Adaptive	31	77.217	2.126
correctly	Driving	Static	29	71.013	2.454
detected		Adaptive	29	73.333	2.126

APPENDIX C

Descriptive Statistics: Dundee Stress State Questionnaire (Subjective Stress)

Measure	Condition	Adaptability	*n*	Mean	Standard Error
Distress	Auditory	Static	31	2.597	0.970
		Adaptive	31	3.371	1.020
	Driving	Static	29	2.879	1.003
		Adaptive	29	2.655	1.055
Engagement	Auditory	Static	31	–4.919	0.988
		Adaptive	31	–4.000	0.912
	Driving	Static	29	–6.500	1.021
		Adaptive	29	–6.155	0.942
Worry	Auditory	Static	31	–2.726	1.043
		Adaptive	31	–2.645	0.952
	Driving	Static	29	0.621	1.078
		Adaptive	29	–0.121	0.984

Note. All values reported as change from baseline.

APPENDIX D

Descriptive Statistics: NASA Task Load Index (Subjective Workload)

Measure	Condition	Adaptability	*n*	Mean	Standard Error
Total Workload	Auditory	Static	30	69.372	1.920
		Adaptive	30	69.328	1.896
	Driving	Static	29	66.328	1.953
		Adaptive	29	63.868	1.928
Physical Demand	Auditory	Static	30	39.667	4.045
		Adaptive	30	40.500	4.313
	Driving	Static	29	29.483	4.114
		Adaptive	29	32.328	4.387
Temporal Demand	Auditory	Static	30	64.583	4.240
		Adaptive	30	65.250	3.953
	Driving	Static	29	53.190	4.312
		Adaptive	29	48.534	4.021
Performance	Auditory	Static	30	57.167	3.848
		Adaptive	30	52.167	3.948
	Driving	Static	29	64.741	3.914
		Adaptive	29	60.000	4.015
Effort	Auditory	Static	30	72.833	3.143
		Adaptive	30	75.083	3.151
	Driving	Static	29	61.034	3.197
		Adaptive	29	62.155	3.205
Frustration	Auditory	Static	30	53.833	4.545
		Adaptive	30	53.917	4.364
	Driving	Static	29	55.345	4.622
		Adaptive	29	52.069	4.438
Mental Demand	Auditory	Static	30	81.917	2.488
		Adaptive	30	81.667	2.718
	Driving	Static	29	80.172	2.530
		Adaptive	29	78.362	2.764

APPENDIX E

Descriptive Statistics: Electrocardiogram

Measure	Condition	Adaptability	*n*	Mean	Standard Error
Heart rate variability	Auditory	Static	30	–2.068	4.623
		Adaptive	30	3.287	3.862
	Driving	Static	27	17.519	4.873
		Adaptive	27	11.160	4.071

Note. All values reported as change from baseline.

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