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Dynamic Task Allocation: Issues for Implementing Adaptive Intelligent Automation

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Abstract

How should tasks be allocated dynamically between people and intelligent machines? What are the initial issues? Previous work on static task allocation and work on human performance when multi-tasking and when interrupted provides suggestions on how to dynamically allocate tasks between humans and machines. We use these results to explore previous theories of task allocation. Some of these theories have direct suggestions for dynamic task allocation and some have indirect implications. We use both types to provide a list of suggestions for creating systems that do dynamic task allocation. The context we will be working with is a type of pilot's associate that has a description of the pilot's tasks and flight mission built within a cognitive architecture. The proposed associate has an additional component that can match the pilot's performance to these tasks, predict the flight phase and pilot's current tasks, and use this information to dynamically allocate these tasks between the pilot and the automation. These suggestions are to inform the design of a high-level intelligent controller.

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1 Introduction

You are designing an advanced intelligent automation system for a new aircraft. This system is being designed to improve the performance of the aircraft during all phases of flight operation and to improve flight safety. What are the characteristics of this system that will meet these goals? What areas of uncertainty exist regarding these characteristics? What research is required to address these uncertainties? We present two scenarios to illustrate a few of the possible considerations that need to be addressed to answer these questions.

> Scenario 1:
>
> During pre-flight operations the pilot is completing his checklist when the tower contacts the pilot regarding a change to the takeoff runway assignment for the flight. The pilot responds to the tower and asks for clarification of the instructions. The pilot returns to the checklist but inadvertently skips several items in the checklist.
>
> Scenario 2:
>
> During pre-flight operations the pilot is completing the preflight checklist when the tower announces a change to the takeoff runway assignment for the flight. The intelligent automation that has been monitoring the pilot s activities and external communications responds to the tower that the pilot is involved in a critical task and asks the tower if their response can be delayed. Given an affirmative response from the tower the automation continues to monitor the pilot s activities and when the checklist is complete it informs the pilot that the tower has contacted them and the pilot should respond. Or, when given a negative response from the tower, the automation notes where the pilot is in the checklist and informs the pilot of the tower communications. When the communications with the tower is completed the automation monitors the pilot s activities to assure the checklist is completed from the point of interruption.

These scenarios highlight a number of important considerations for the design of intelligent automation for aircrew support. One aspect that is highlighted is the extent and depth of the knowledge developed and maintained by the automation of the current context, the overall mission goals and standard cockpit activities, and the goals and intentions of the human aircrew. A second aspect involves when to interrupt the aircrew s current activities either to provide important information or to request a command decision. A third aspect involves a monitoring function performed by the automation to assure that critical tasks being performed by the aircrew are performed correctly.

Each of these capabilities already exists in semi-automated cockpits. By intelligently allocating tasks dynamically, it should be possible to improve performance as the mission evolves and the requirements on the joint human-automation system change. Future work will help determine which of these scenarios will occur in cockpits that attempt to introduce increasing intelligent automated support for the human aircrew and provide for dynamic allocation of tasks between the pilot and automation aids. We review here what is known about how people dynamically allocate tasks.

Automation was originally expected to reduce the workload on the human in the system. However, the impact of automation on the workload characteristics of the human agent is far more complex. As nearly every researcher finds, automation does not simply reduce the workload, rather it redistributes the workload and causes fundamental changes in the character of the operator work. Automation also forces new communications and coordination requirements on the human.

Automation has been found to primarily support the human during routine phases of operation (when the human workload is relatively low) but generally fails to provide support under dynamic critical phases of operation when support for the human is most crucial. Automation in many instances relieves the operator of tasks at times when he already has a light workload but during periods when the workload is high and time is short it may add to his workload or even impede his effort.

This report approaches dynamic task allocation in three different ways. First, we review previous studies, commentaries, and reviews. The previous reports suggest issues that must be kept in mind when dynamically allocating tasks. And as it is an important subtask, what happens when humans are interrupted when they work in a complex multi-tasking environment. The literature that we are aware of does not provide a complete theory of how to allocate tasks dynamically between humans and machines, but these prior studies and reports, taken together, start to provide guidance and important suggestions as to the salient features.

Second, we can take these issues and examine how these issues are related to theories of human problem solving and performance, such as is implemented in the ACT-R cognitive architecture and existing theories of task allocation. As we do this we find that there are additional issues, problems, and complexities in dynamic task allocation.

We will first note several of the numerous issues that have arisen in previous studies on task allocation and on dynamic task allocation. We will use these issues to explore previous theories of task allocation. Some of these theories have direct suggestions for dynamic task allocation, and some suggestions that can be derived. We will use both to provide a list of suggestions for creating systems that do dynamic task allocation.

Finally, we examine several studies on task allocation in general and dynamic task allocation in particular. Overall, the review, the theories, and the data make several suggestions for implementing and improving dynamic task allocation. Most importantly, in the design of systems with dynamic task allocation it is necessary to be particularly careful about the communication of task status and task allocation.

Awareness of each team member s status and progress, and the environmental context are also important.

The context we will be working with is a type of pilot's associate that has a description of the pilot's tasks and flight mission built within a cognitive architecture. The associate has an additional component that can match the pilot's performance to these tasks, predict the flight phase and pilot's current tasks, and use this information to dynamically allocate these tasks between the pilot and the automation. These suggestions are to inform the design of a high-level intelligent controller and to note what features to attend to in order to improve this allocation over time

2 Issues in Dynamic Allocation of Tasks among Humans and Machines

Numerous authors have written about problems in allocating tasks between humans and machines. In this section we review several of the most salient issues and problems that have been identified after first defining some terms and providing an overview.

Currently, there is a desire for automation to assist with work through dynamically allocating tasks as well as doing them. There are two possible ways this has been considered. The most common is for the automation to dynamically allocate the tasks and most of the work reviewed here takes that approach. The other approach is to allow the user to allocate the tasks. This is a theme we will come back to in the conclusions (if not before). The former view, with the automation having more control, is better studied.

The fundamental characteristic of all function allocation methods is that the system and the goals (e.g., the mission) can be decomposed. One hierarchical structure for representing human engineering analysis presented in Beevis (1999) is:

(a) Mission and Scenario Analysis
(b) Function Analysis
(c) Function Allocation
(d) Task Analysis
(e) Performance Prediction
(f) Interface and Workspace Design

The higher level functions are considered to be composed of tasks, and tasks are often viewed as the concrete tangible activities (opening a valve or extending the flaps), whereas functions are viewed as more abstract.

Function allocation refers to the distribution of function among humans and machines in complex technological systems such as aircraft cockpits. Function allocation is inherent in the use of automation and results from the decision to introduce automation into the system even if the allocation of function is not explicitly considered (Hollnagel & Bye, 2000).

For systems involving human agents and automated agents, dynamic function allocation has been described as the redistribution of tasks or functions among these agents in order to facilitate the attainment of one or more common system goals or objectives (Campbell et al.). Dynamic function allocation presupposes that both the human and the machine have the capability to perform the function. This redundancy among human and machine for performing similar functions has been termed function congruence (Hollnagel, 1999). The allocation is typically done in response to some change in the system environment or context such as a change in the workload of the human agent. The dynamic reallocation of functions between human and automated agent is often referred to as adaptive automation.

2.1 The benefits and problems of automation

Parasuraman (1997) has identified four types of problems that can arise when automation is used:

(a) Loss of expertise — whenever a function or task previously performed by the human is allocated to automation there is a loss of skills on part of the human in performing the task should the need arise. Under abnormal conditions, when the human is required to take over these tasks, the human s skills and situational awareness may have become sufficiently degraded to seriously diminish their ability to perform the task in a timely manner.

(b) Complacency — Trust resultsfrom the gradual acceptance of the reliability of the automation over time with successful performance. There are both negative and positive aspects of this growing trust. Overestimating the reliability of the automation can lead to complacency and a false sense of security in the infallibility of the system. A human operator may come to overly trust highly reliable, but still imperfect automation. Under these conditions the operator may fail to monitor the actions of the automation and fail to detect instances when the automation fails. Complacency is a function of an operator s trust, reliance on, and confidence in the capabilities of the automation (Singh, Molloy, & Parasuraman, 1993).

Moray (1999) however, suggests that failure to monitor is more likely to be a eutactic strategy rather than complacency and that alarms rather than monitoring may be more important for the efficient supervisory control of highly reliable systems. Moray defines complacent behavior as behaviour that samples less frequently than is specified by some optimal strategy. Eutactic behavior is sampling that matches an optimal (or at least a satisficing) frequency and which ensures optimal (or at least satisficing) performance in detecting signals.

(c) Lack of Trust — The reliability of the automation is central to the human operator developing trust in the system and the willingness of the human to use the automation. Automated systems may not be fully utilized or not used at all if the level of mistrust resulting from poor reliability is high.

(d) Loss of Adaptivity — System designers have often designed the actions and functions of automation in such a manner that the normal adaptive behavior of human cognition is thwarted and frequently becomes counterproductive to the actions of the automation. Designers that conceive of human cognition as a purely reactive system neglect the human s expectations of future events and the feedback that is necessary for adaptation.

Dekker and Woods (1999) provide a summary, shown in Table 1, of the purported benefits of the introduction of automation and the realties associated with its introduction.

Table 1. Benefits and Challenges of Automation, taken from Dekker and Woods (1999).

Putative benefit	Real complexity
Better results, same system (substitutional)	Transforms practice, the roles of people change
Offloads work	Creates new kinds of cognitive work, often at the wrong time
Focuses user attention on the right answer	More threads to track; makes it harder for practitioners to remain aware of all the activities and changes around them
Less knowledge required	New knowledge and skill demands
Autonomous machine	Team play with people is critical to success
Same feedback support	New levels and types of feedback are needed to support peoples new roles
Generic flexibility	Explosion of features options and modes create new demand types of errors and paths toward failure
Reduces human error	Both machines and people are fallible; new problems associated with human-machine coordination breakdowns

2.2 Ironies of automation

In a now well known chapter, Bainbridge (1987), wrote about the ironies of automation, how taking away the easy parts of the user's tasks, the parts that automation can handle, can make the difficult parts of the user's tasks more difficult. Through example and argument from first principles she makes the case that automation can lead to problems through several mechanisms, many of which are reported as problems by other authors. These problems include (a) how manual control skills and cognitive skills related to problem solving deteriorate without practice. When the user must help the automation, these skills are less practiced. (b) With less hands-on practice with the system, the user has a poorer mental representation of the system and how it responds to inputs. (c) The user monitoring a system being controlled by automation has poorer situation awareness than a user manually controlling the system. (d) The task that is most often passed to the human user, that of monitoring a system and looking for anomalies, is a vigilance task, one of the most difficult tasks for a human to perform for long periods of time.

Bainbridge proposes several solutions for dealing with these factors. The first is better use of displays and alarms to support the user in their monitoring task. These displays should also provide additional state information, similar to Wood's later arguments. One particular problem to avoid is masking a system moving towards a catastrophic failure without the user being aware of the systems movement until the automation completely fails, leaving the user to sort out a particularly nasty state. Second, the automation must progress at a pace the user can follow and monitor. Third, an ironic suggestion itself, is for the automation to fail more often to keep the user more vigilant. Finally, practice on simulators on the hard and rarer problems is seen as a partial solution.

2.3 Automation as team player

The introduction of automation into a system explicitly changes the characteristics of the system and fundamentally changes the nature of the interactions in the system. The automation is much more than a substitute for human activities. Sarter and Woods (1997) suggest that introduction of semi-autonomous machine agents is like adding a new team member. This results in new coordination and communication demands on the existing team members because the performance objectives of the system are not met by the individually agents working independently but through the coordinated activities of the humans and machine agents (Christoffersen & Woods, 2002).

Hence, cooperating automation is a good team player when it is both observable and directable (Christoffersen & Woods, 2002). If it is difficult for the human team members to observe the actions and intentions of the automation or it is difficult to direct the automation then the coordination demands on the human team members are magnified. If advanced automation is introduced into the system with increased autonomy and authority and without considering the requisite increase in coordination then the result often is automation surprises (Christoffersen & Woods, 2002).

Observability includes development of a shared mental model of the problem or task being performed and of the current context (situation). Furthermore, the human agent must understand what activities the machine agents are engaged in to further the goals, why they are performing these actions, what they likely are going to do next, and indications of the success or difficulties they are having in the performance of these activities. Christoffersen and Woods (2002) indicate that new forms of feedback in the form of pattern-based representations of automation activities will be required to balance the new levels of agent autonomy. This feedback includes event-based representations that highlight changes and events, that indicate what changes and events will occur next and how soon, that integrate data into meaningful patterns that can be quickly understood, and that support re-orienting attention to important events. More information is available to the operator today than was available in the past, but the methods used to present this information do not match the information-processing capabilities of the operator and do not facilitate the operator s understanding of the information in the context of what he needs to know (R. Amalberti & Sarter, 2000; Dekker & Woods, 1999; Howard, 1999). The interfaces for current generation of automated systems are designed for data availability rather than data observability.

Directability involves the capability for the humans to intervene and change the characteristics of the machine agent s activities. Generally, past intervention by humans has been of an all or none variety where the human could intervene to take complete manual control of the activity from the automation. However, this approach does not take advantage of the capabilities of the automation acting in a subsidiary role and places the full workload for the activity on the human. Christoffersen and Woods (2002) recommend an intermediate cooperative mode of interaction, which allows the human to direct the automation to perform sub-problems or to interject solution approaches that the automation was not preprogrammed for. A critical area to address is the development of techniques for communicating the intent of the machine agents to human users including the agent s target(s) and goals, and its constraints.

2.4 Automation surprises

Automation surprise is a term that was coined for the circumstances when the automation takes some action that the human was not prepared for or does not understand. There is a divergence between what the operators expect the automation to be doing, or to do, and what the automation actually is doing, or will do (Dekker & Woods, 1999). The human operator typically is asking questions such as: What is it doing now? Why did it do that? What is it going to do next? (Wiener, 1989). The human is unable to assess the current situation as a result of insufficient information from the automation.

Automation surprise appears to be most prevalent with automation that can autonomously make decisions (e.g., change flight mode) without the consent of the operator and without clear feedback from the system to the user that changes have been made. To minimize the potential for automation surprises under these conditions Dekker and Woods (1999) suggest that the human operator must:

- have an accurate model of how the system works,
- call to mind portions of their knowledge that are relevant to the current situation,
- recall past instructions that may have occurred some time ago and may have been provided by someone else,
- be aware of the current and projected state of various parameters that are inputs to the automation,
- monitor the activities of the automated system, and
- integrate all this information and knowledge together to assess the current and future behavior of the automated system.

This list emphasizes the complexity of the impacts on human cognition and human workload when autonomous automation is introduced into the human-machine system.

An important observed behavior of complex human-machine automated systems under infrequently occurring, off-normal, and often critical situations where the cognitive and coordination demands on the system rapidly escalate is that the automation is ill-designed to support the human agents and often adds to the human agent workload rather than providing support. The automation is often brittle under these conditions.

2.5 Cooperation

Cooperation is often defined as the joint activities of multiple agents toward a common goal. However, when one or more of these common agents is a machine it is not clear if, and how, the machine agent maintains a representation of the overall common goal. Noting the asymmetric nature of human-machine cooperation, Hoc (2001) has defined cooperation as:

Two agents are in a cooperative situation if they meet two minimal conditions.

> (1) Each one strives towards goals and can interfere with the other on goals, resources, procedures, etc.
>
> (2) Each one tries to manage the interference to facilitate the individual activities and/or the common task when it exists.

The symmetric nature of this definition can be only partly satisfied.

In the definition above interference refers to any interactions among the agents that may impact the activities of the other agents either in a positive (facilitation) or negative manner. Hoc (2001) identifies the following types of interference:

a. Precondition interference _ This type of interference relates to the activities that one agent must perform in order for another agent to perform his particular activities.
b. Interaction interference — These are contemporaneous activities performed by agents that may support or conflict with the actions taken by other agents and must be coordinated.
c. Mutual control interference — The activities of one agent are monitored and checked by a second agent and when a disagreement arises a method for consensus is implemented.
d. Redundancy interference — Under conditions when it is not clear which agent is most capable of performing a task the task may be allocated to two or more agents with different capabilities.

2.6 Supervisory control/decision authority

It is generally considered a central principle in automation design that the final responsibility and authority for decisions and control must reside in the human members of the system. Because humans bear the ultimate responsibility for the performance of the system they must be presented with adequate information and control to intelligently exercise this authority. Hence, the humans need to be involved (kept in the loop) and informed about the current situation and intended actions by the automation.

Sheridan (1992) proposed a breakdown in the degree of control among humans and machine that ranges from complete manual control to fully autonomous machine control. Scale of levels of automation from Sheridan (1992) that provides a description of the levels of authority:

1. The computer offers no assistance, human must do it all.
2. The computer offers a complete set of action alternatives, and
3. narrows the selection down to a few, or
4. suggests one, and
5. executes that suggestion if the human approves, or
6. allows the human a restricted time to veto before automatic execution, or
7. executes automatically, then necessarily informs humans, or
8. informs him after execution only if he asks, or
9. informs him after execution if it, the computer, decides to.
10. The computer decides everything and acts autonomously, ignoring the human.

Inagaki (1999) argues that there are certain situations where it is proper that final authority reside in the automation itself. He argues that under situations where system safety is involved the automation may be given the authority to take an automatic action even when an explicit instruction has not been received from a human. He gives examples of control actions that are performed automatically in nuclear power plant control rooms such as reactor trip and initiation of emergency coolant injection. Under conditions where the control actions must be taken in a very short time period to avoid catastrophic consequences, such as aircraft collision avoidance, it may be appropriate to allow autonomous control actions. He also argues that under conditions when the operator is not highly trained (non-professional) it may also be appropriate to allow the automation to make decisions autonomously.

Although Iganaki s arguments contain valid points it should be recognized that the basic principle that the human has overall responsibility has not changed. In situations where a decision has been made to allow autonomous control action by the automation the responsibility has been removed from local human operator and has been transferred to the system designer or organizational management.

2.7 Situation/state/mode awareness

Situation awareness (SA) can be defined as an internal mental model of the current state of the system and its environment. SA includes not only the immediate perception of data, but also the understanding of the significance of this data on potential future states of the system and environment (M. R. Endsley, 1999). Situation awareness involves perceptual, diagnostic, and inferential cognitive processes. Endsley presented a formal definition of SA as the perception of the 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 identifies three levels of SA:

Level 1 — perception of the important elements in the environment
Level 2 — comprehension of the current situation based on an integration of the perceived environmental elements, the understanding of the function and operation of the system and the interactions of the system and the environment
Level 3 — projection of the future status of the system and the environment

Problems with situation awareness are the major causal factor in both civilian and military aviation accidents (M. R. Endsley, 1999). Endsley (1996) indicates that automation impacts SA through three major mechanisms;

1. Changes in vigilance and complacency associated with monitoring,
2. Assumption of a passive role instead of an active role in controlling the system, and
3. Changes in the quality or form of feedback provided to the operator.

Mode awareness is a particular type of situational awareness that has been studied in some detail. Degani, Shafto, and Kirlik (1999) define mode as as a machine configuration that corresponds to a unique behavior . A mode is an enumerated grouping of machine configurations and behaviors. Mode changes may be triggered by specific operator commands or automatically by the machine. A particular type of loss of situation awareness occurs when the automation can change operating modes based on internal setpoints or triggers without the express consent or without formal notification of the human controller and hence without the human recognizing that a mode transition has occurred in the automation. This is a particularly controllable loss of situation awareness.

Degani (1997) identifies three classes of modes associated with human-systems interactions. As they described it [italics as in original]:

1. *Interface* modes that specify the behavior of the interface,
2. *Functional* modes that specify the behavior of the various functions of a machine, and
3. *Supervisory* modes that specify the level of user and machine involvement in supervising the process.

Mode ambiguity occurs when the input or control actions have different meaning or effects depending upon the particular system mode. Mode error can result from mode ambiguity when the user s expectations regarding an action differ from the actual responses of the system to the action.

Mode ambiguity and mode related errors can be greatly reduced if the human has developed a robust mental model of the automation that facilitates identification of the current mode of the machine and the future modes of the machine given a manual input or automation triggered event. This mental model requires an understanding of which events or parameters and their thresholds trigger a mode transition and information regarding the current event state and triggering parameter values (Degani et al., 1999). The interface must provide the required information or there is little chance that the operator, even with a sound mental model, will be able to assess machine configurations reliably.

2.8 Multi-tasking

Multi-tasking is the rule rather than the exception in aviation. Multi-tasking involves performing several tasks concurrently, shifting cognitive resources among the competing tasks being performed. A military pilot simultaneously controls the aircraft, communicates with other aircraft and air traffic control, monitors his instrumentation, watches for other aircraft or missiles in the air, monitors his altitude and proximity to ground based obstacles, executes mission requirements, and fires his weapons.

Attention is important when considering multitasking. The National Research Council s Panel on Modeling Human Behavior and Command Decision Making (1998) indicate that attention can be understood as the means by which scarce or limited processing resources are allocated to accomplish multitasking. They enumerate three types of attention:

1. Selective attention — process of selectively allocating processing resources to some things at the expenses of others,
2. Focused attention — process of rejecting some things in favor of others,
3. Divided attention — a situation wherein the human attempts to carry out many processes simultaneously, distributing resources among them.

When the human in a multitasking environment becomes overloaded several potential outcomes may result. He may:

1. Continue to try to attempt to do all task but perform them less well,
2. Drop some tasks,
3. Develop a ordering queue,
4. Stop performing all tasks, or
5. Batch tasks (Kuk, Arnold, & Ritter, 1999)

An issue closely related to multitasking and attention is interruptions. Interruptions occur when an individual is caused to change the focus of his current attention and activity, usually as a result of an external sensory input. Generally, interruptions are initiated by fellow humans, either in the immediate vicinity or remotely (as in attending to a radio communication), or by the control or automation system. The interruptions may be of advisory nature, such as a warning of some system malfunction or low fuel level, or may request input from the human such as a supervisory decision. Interruptions are an inevitable result of a complex control system involving multiple intelligent agents (human and machine) in a multitasking environment. Dynamic task allocation will require interruptions to be addressed, although there may be ways to avoid or ameliorate interruptions.

McFarlane (1998) provides a formal definition of human interruption as the process of coordinating abrupt changes in people s activities.   He also provides a detailed taxonomy of interruptions.

As McFarlane (1999) has noted, interruptions are problematic since people have cognitive limitations that restrict their ability to work during interruptions. He suggests that it is necessary to reconsider the design of interfaces such that these limitations are acknowledged and that interruptions are allowed to occur in a manner that does not compromise mission safety. One critical aspect of interruption, which he has called the Method of Coordination involves the technique used to decide when to interrupt people. He identifies four ways of coordinating interruptions:

1. Immediate — Interruptions occur at any time and must be handled immediately.
2. Negotiated — An interruption is requested and the human chooses whether to, and when to, handle the interruption.
3. Mediated — A third party screens all requests for interruptions and determines whether or not to notify the human.
4. Scheduled — Interruptions are allowed only at certain times (or after certain elapsed time periods).

It should be noted that negotiated interruptions have additional cognitive overhead in that the act of negotiating a request for interruption is itself a task that must be attended to and hence the human s attention has been changed to this intermediate task. As Adams and Pew (1990) have noted, To notice the occurrence of an event in any useful way, the pilot must immediately interrupt ongoing activities, at least to evaluate its significance, and establish the priority of its response implications. Resumption of the interrupted task must require thoughtful review of its status and may require repetition or reinitiation of one or more of its procedural components. Thus, the very reception of unanticipated data must always introduce an additional and disruptive element of workload. The design implications, especially for time-critical systems, should not be ignored.

2.9 Affective state

The human s affective state can have a significant effect on performance and potential for error. Recent research indicates that emotion can have a profound influence on cognitive processing and behavior. Affective state can influence perceptual, cognitive and motor processes including memory and attention and higher-level processes such as situational assessment, decision-making and judgment. For a review see Hudlicka and McNeese (2001) or the Panel on Modeling Human Behavior and Command Decision Making: Representations for Military Simulations (1998).

Fear and anxiety influence attentional focusing processes and perception, enhancing the detection of threatening stimuli (Hudlicka & Corker, 2001). The extent of the effect of affective state depends on the individual, the task and on the context. They suggest that there are other contextual factors that determine the extent of the influence of affective state including skill level, general cognitive abilities, individual history, prior experience with the task and current interpersonal environment.

Hudlicka and Corker list the following questions regarding emotions and their role in human behavior and their influence on operator control modes:

- What is the function of emotions? What role do they play in behavior and adaptation?
- How do individual differences and distinct personalities influence cognitive-affective interactions? How does this vary across situational contexts?
- What are the exact effects of traits/states on individual cognitive and perceptual processes and structures? What is the causal sequence of these interactions?
- How can the knowledge of these processes inform more error-resistant human-system designs?
- How can existing human performance models, user modeling, and adaptation methods be applied to affective adaptation? What emotions *should* and *can* be recognized, modeled, and adapted to human-machine interfaces?
- How does the computational representation of competence interact with the representation of affective states and personality traits?
- Under what circumstances should the system attempt to enhance the user s affective state, when should it adapt to the user s affective state, and when should it attempt to counteract it?

3 Theories of Task Allocation

Several theories of how tasks should be allocated between the user and the automatic aids have been proposed, more than can be fully reviewed here. We examine a few representative ones, as well as using a cognitive architecture to examine the issues of how to dynamically allocate tasks.

We include the topic of interruptions because as the tasks are allocated dynamically, communication between the automation and the user will have to occur. As the communication of the automation to the user has to be about tasks the user is not performing, these communications have some aspect of interruption about them.

3.1 Human information processing models

Hollnagel (2000) suggest that there are two fundamentally different categories of human information processing models; linear and cyclic. A specific example of a cyclic model called the four stage model is described.

3.1.1 Linear models

The first model generally considers events to occur in a linear fashion with the human responding to current sensory inputs (communications, events, signals) and producing actions to effect system responses based on these inputs.

3.1.2 Cyclic models

The second model views the human processor in a cyclic pattern where the implications of future actions are considered as well as the empirical results of prior actions in the cognitive process (Hollnagel & Bye, 2000). The cyclic model contains an extended notion of time — there exists a past (a history), a present, and a future. The cyclic model emphasizes the importance of the human s current understanding of the situation (state of the system) and how past actions and events have shaped the situation and how future actions may change the situation. In the aviation domain loss of this understanding of the current situation by the pilot as a result of the effects of automation has been called taking the pilot out-of—the-loop.

In the cyclical model the human tasks of evaluation and acting are continuous and coincidental. This facilitates the representation of disruptions or interruptions in execution of a plan (an ordered set of intended actions for performing a task), multi-tasking (the performance of interleaved plans) and the impact of focused attention on a single task on the performance of other tasks.

3.1.3 Four stage model

Parasuraman et al (2000) propose a four-stage model for human information processing to cover automation of different types of functions in human-machine systems. These stages are:

1. Acquisition and registration of information — positioning of sensory receptors, sensory processing, pre-processing of data prior to full perception and selective attention,
2. Conscious perception and information analysis — manipulation of information in working memory including rehearsal, integration and inference,
3. Decision and action selection, and
4. Implementation of response or action.

These four stages are considered to be coordinated in perception-action cycles rather than in a strictly linear manner and there is overlap and inter-dependence in the various stages. Each of these four functional stages can be automated to a different extent. They suggest the use of the ten levels of automation proposed by Sheridan (1992) and discussed in section 2.6. The primary metric for assessing which level of automation is appropriate is the human performance consequences of that level of automation. Secondary evaluation criteria are the reliability of the automation and the costs of decision/action consequences . The costs of the decision/action outcome refer to the consequences resulting from incorrect or inappropriate actions.

The human performance consequences to be considered include (Parasuraman et al., 2000):

1. Mental workload
2. Situation Awareness
3. Complacency

4. Skill Degradation

3.2 ACT-R's cognitive mechanisms

ACT-R is a theory of human cognition developed by Anderson and his colleagues (Anderson & Lebiere, 1998) - also see act.psy.cmu.edu for an online tutorial). It is a unified theory of cognition, in the spirit proposed by Newell (1990) in that it is designed to predict human behavior by processing information and generating intelligent behavior itself. As such a theory, it makes suggestions about when and how tasks should be allocated to human users.

The major components of ACT-R are shown in Figure 1. Information is received through a perceptual, typically visual, system, indicated schematically on the bottom right of the figure. The objects identified by perception are processed by a production system (center) that matches patterns and modifies internal buffers. These buffers include buffers for goals (upper left), for perceptual information, and for declarative memory (upper right). Finally, the results of processing can be put into an output buffer for output through the motor system.

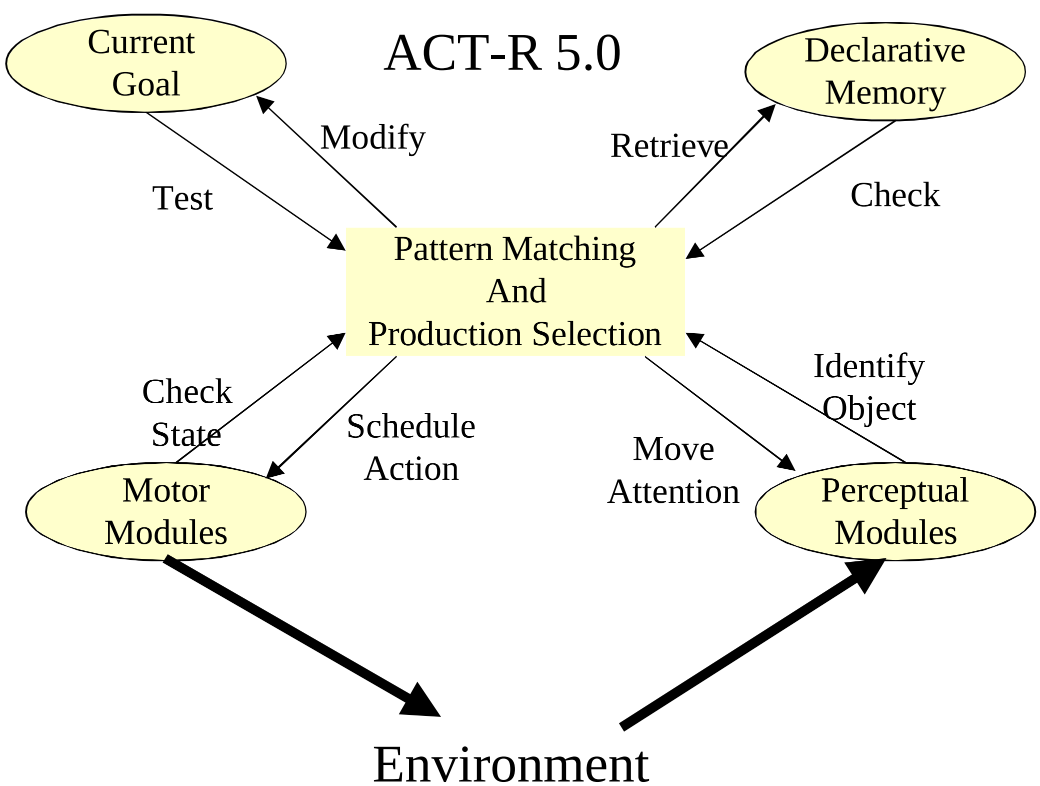

Figure 1. A schematic of the major components of ACT-R. Reprinted with permission of Lebiere.

These buffers typically include full, detailed theories themselves, and are based on published data from psychology studies. The perceptual and motor buffers, for example, are based on an existing theory of perception and motor action (Byrne, 2001).

These mechanisms, as summaries of human behavior, make several suggestions about when and how to allocate tasks to the user represented with these components, and when to interrupt the user.

Users will typically be performing multiple tasks based on their goals, which may be represented in the Current Goal buffer as well as in declarative memory. They will be encoding information from perception, and using the resulting encoded objects to work towards their current goal.

ACT-R suggests that the best way to perform dynamic task allocation and schedule interruptions will depend on the tasks and the user's task knowledge representation. Suggestions for optimal performance from previous studies may be tied to those studies tasks and user knowledge sets. Learning can also be important.

3.2.1 When task switches would be least disruptive

There are several places where interruptions would be the least disruptive. Examples of such temporal location are interrupting at the end of a task that does not need its goal augmented or saved, and interrupting after the goal has been augmented or saved. Interrupting by putting a flag up in perception that leads to the appropriate rules matching and taking the new information in at an appropriate user chosen time, such as at the end of an internal task, would also be appropriate.

Dynamically taking the entire current goal from the user might also be minimally disruptive in terms of the architecture. The goal could be popped and passed out via the motor commands. If it did not have to be monitored, this should not be very disruptive.

Dynamically allocating a task would be best done where the task being removed (or added) to the user's list of tasks maps fairly directly onto the task knowledge in the user's head. That is, moving tasks that are represented relatively the same in the user s head as well as the world, and are modular will be easier to keep track of by both the automation and the user than tasks that require problem solving and representation by the user.

Leaving the user with tasks that use different parts of the architecture would be desirable. Sets of tasks that use more of the architecture in parallel will provide more throughput, although the same must be said for automation architectures as well. For example, using speech input for one task and vision input for another will allow expert users, at least, to process more information.

3.2.2 When task switches would be disruptive

The ACT-R architecture suggests that there are several places where interruptions would be particularly disruptive. If the interruption leads to modifying a motor output in process, then the motor output will be lost. If an interruption occurs when a goal is being transferred from the current goal buffer to declarative memory (because a subgoal is being created), or during rehearsal of a goal, could lead to losing that current goal.

An interruption or task allocation should not occur when a perceptual object that should lead to a goal is being encoded into a goal. Interrupting at this time, if the perceptual object disappears, could lead to not performing the appropriate task.

Reallocating a task that has several similar sub-tasks would be more difficult; the similar tasks are likely to be retrieved along with the goal, and are likely to be wrongly updated in the process. Interruptions that occur in the middle of a set of actions can disrupt those actions if they are represented as a set of goals in declarative memory and the order is critical but still not well learned. At the time of the interruption, the goals should have rather different activations and be retrievable in order based on those differences. The time spent processing the interruption will allow the goals to decay, and with the exponential decay, become more similar in activation, leading to confusions in retrieval. An example model of this has been created by Schoppek et al (2001).

3.2.3 Supporting behavior across interruptions

Altmann and Trafton's (2002) ACT-R model of a problem solving task showed that some errors in performance arise because the correct goal to work on is not always retrieved from working memory. The retrieval failure can be caused by not having the correct goal active enough, or through noise in the retrieval process that allows a similar goal or a nearly equally active previous goal to be retrieved. Errors will increase in larger tasks because there are more goals and a greater reliance on memory to keep track of goals.

Altmann and Trafton's theory (2002) suggests several ways to reduce these errors. Allowing the user time to encode and strengthen goals upon interruption can ameliorate some of the problems of interruptions because the correct goal can then be recalled when the task is resumed. Providing cues to resume the task as well as generally using external memory aids is also useful.

More concretely, the interruptions must themselves be paced, the user must take time to save their current task, perhaps and commonly by encoding a retrieval cue using the environment. Good retrieval cues are thus also important. The cue must be available as the task is taken back up. Keeping state knowledge, in the world, and in your head is thus important when being interrupted.

3.2.3 Learning when to interrupt

Learning by the user will make knowing when to interrupt more difficult. With learning users will become faster at subtasks, will strengthen their declarative memories, and can change their strategies.

With learning, the user will be able to handle interruptions more gracefully. With additional expertise they will have more capacity for task performance, they will process information faster and they will be able to keep the objects in declarative memory in mind better.

An observing system might also be able to learn when to interrupt. This system would be attempting to learn the internal steps the user was performing in order to find when a subtask switch had occurred. Observing the motor output (including speech) and perceptual input while having a model of the user's internal state and processes would be required for learning.

3.3 General theories of task allocation

3.3.1 Left-over principle

Early strategies for function allocation allocated all those functions to the machine that were technically and economically practicable to automate. The underlying assumption was that humans are inherently unreliable and/or inefficient, and that overall system performance would be improved by automating all possible tasks. The human was then allocated those functions that could not be, or were not, automated. This strategy has been called the left-over principle. Implicit in this approach was the assumption that automation could be substituted for human actions without any significant impact on the overall system (Sarter et al., 1997). There was little consideration given to whether, or how well, the human could effectively perform these remaining non-automated tasks.

3.3.2 Compensatory principle/Fitts list/MABA-MABA

Fitts (1951) introduced the first systematic approach to joint allocation of functions between human and machine. This approach, often called the complimentary approach or MABA-MABA (men are better at-machines are better at), was based on an assessment of the relative strengths and weaknesses of humans and machines, and functions and responsibilities were allocated based on this assessment. It has been noted that the principles on Fitts list are static and consequently are ineffective for dynamic task allocation (Sheridan, 2000).

Table 2. The Original Fitts (1951) List.

Humans appear to surpass present-day machines with respect to the following:°

- Ability to detect small amounts of visual or acoustic energy
- Ability to perceive patterns of light or sound.°
- Ability to improvise and use flexible procedures.°
- Ability to store very large amounts of information for long periods and to recall relevant facts at the appropriate time.°
- Ability to reason inductively.°
- Ability to exercise judgment.°

Present-day machines appear to surpass humans with respect to the following:°

- Ability to respond quickly to control signals, and to apply great force smoothly and precisely.
- Ability to perform repetitive, routine tasks.
- Ability to store information briefly and then to erase it completely.
- Ability to reason deductively, including computational ability.
- Ability to handle highly complex operations, i.e. to do many different things at once.

3.3.3 Complimentarity principle

A third approach to function allocation called the complementarity principle (Grote, Weik, Wafler, & Zolch, 1995) is directed at maintaining human control of the situation and on the retention of critical human skills. This approach views function allocation not as competition among the human agents and machines based competency in performing the task or that the automation is a replacement for the human. It emphasizes the means by which humans and machines can complement each other.

3.3.4 Complemation

Schutte (1999) presents the concept of complemation. He defines complemation as complementary technology that is designed to enhance human skills and abilities rather than replace them. Complemation emphasizes that the machine be used principally for monitoring and implementation and the human operator focuses on high-level decision-making. The human is always engaged in the important activities and thus develops the appropriate situational awareness. Machines should be used to support humans in areas of human frailty such as poor memory recall, poor vigilance, and lack of precision and support the human areas of strength such as ability to develop novel solutions under unanticipated conditions. Schutte is particularly sensitive to the traditional automation approach of relegating monitoring duties to the human operators, which he argues have been demonstrated to be inherently poor monitors of highly reliable systems.

Schutte argues that nowhere is the difference between automation and complemation more apparent than in function allocation. He argues that the human operator should always be involved at a high level and in a meaningful way in all important tasks so that he remains vigilant (does not become complacent because of high system reliability), develops and maintains the correct situational awareness and maintains skills necessary for troubleshooting. This argument suggests that many tasks that could be automated (or have been automated) should deliberately not be automated to so that the human remains involved in the task. Schutte indicates that the function allocation scheme suggested by Endsley (1999) addresses the principles of complemation (section 3.3.5).

Increasing the role of the human in the joint-system has the potential to increase the risk of human-induced errors, however Schutte argues that one of the main functions of the machine should be to monitor and catch, counteract, and compensate for these errors. The machine should also provide differing levels of augmentation for individual with different levels of skills and abilities.

3.3.5 Levels of automation

Endsley (1999) developed a 10 level taxonomy of levels of automation (LOA) that can be applied to a wide variety of cognitive and psychomotor tasks within domains characterized by:

- multiple competing goals,
- multiple tasks competing for an operator s attention, each with different relevance to system goals,
- high task demands under limited time resources.

Four functions types that can be allocated to the human or machine that are intrinsic to these domains were identified as:

- *monitoring* — scanning displays to perceive system status;
- *generating* — formulating options or strategies for achieving goals;
- *selecting* — deciding on a particular option or strategy;
- *implementing* — carrying out the chosen option.

Table 3 shows the 10 level taxonomy created by assigning these functions to the human or the machine or to a combination of human and machine.

3.3.6 Level of automation

Sheridan (2000) argues that his 10 levels of automation (section 2.6) have been interpreted too strictly, that automation and control are multi-dimensional, and that task complexities are not completely captured by the one-dimensional representation of the 10 level scale. He indicates that the optimal level of automation is likely different for different stages of task performance, and one should not assume *a priori* that a single level of automation is appropriate for all stages of a complex task. In conjunction with a revised 8-level scale of automation (reduced from the 10-level scale shown in section 2.6) he proposes the use of a four stage task model:

1. information acquisition,
2. analysis and display,

3. decide action, and
4. implement action

For each stage in the task a different level of automation may be appropriate.

Table 3. Hierarchy of levels of automation from Endsley (1999).

	Roles			
Level of automation	Monitoring	Generating	Selecting	Implementing
(1) Manual control	Human	Human	Human	Human
(2) Action support	Human / Computer	Human	Human	Human / Computer
(3) Batch processing	Human / Computer	Human	Human	Computer
(4) Shared control	Human / Computer	Human / Computer	Human	Human / Computer
(5) Decision support	Human / Computer	Human / Computer	Human	Computer
(6) Blended decision making	Human / Computer	Human / Computer	Human / Computer	Computer
(7) Rigid system	Human / Computer	Computer	Human	Computer
(8) Automated decision making	Human / Computer	Human / Computer	Computer	Computer
(9) Supervisory control	Human / Computer	Computer	Computer	Computer
(10) Full automation	Computer	Computer	Computer	Computer

1. *Manual Control* (MC) — the human performs all tasks including monitoring the state of the system, generating performance options, selecting the option to perform (decision making) and physically implementing it.
2. *Action Support* (AS) — at this level, the system assists the operator with performance of the selected action, although some human control actions are required.
3. *Batch Processing* (BP) — although the human generates and selects the options to be performed, they then are turned over to the system to be carried out automatically. The automation is, therefore, primarily in terms of physical implementation of tasks.
4. *Shared Control* (SHC) — both the human and the computer generate possible decision options. The human still retains full control over the selection of which option to implement; however, carrying out the actions is shared between the human and the system.
5. *Decision Support* (DS) — the computer generates a list of decision options that the human can select from or the operator may generate his or her own options. Once the human has selected an option, it is turned over to the computer to implement. This level is representative of many expert systems or decision support systems that provide option guidance, which the human operator may use or ignore in performing a task. This level is indicative of a decision support system that is capable of also carrying out tasks, while the previous level (shared control) is indicative of one that is not.
6. *Blended Decision Making* (BDM) — at this level, the computer generates a list of decision options that it selects from and carries out if the human consents. The human may approve of the computer s selected option or select one from among those generated by the computer or the operator. The computer will then carry out the selected action. This level represents a higher level decision support system that is capable of selecting among alternatives as well as implementing the second option.

7. *Rigid System* (RS) — this level is representative of a system that presents only a limited set of actions to the operator. The operator s role is to select from among this set. He or she may not generate any other options. This system is, therefore, fairly rigid in allowing the operator little discretion over options. It will fully implement the selected actions, however.
8. *Automated Decision Making* (ADM) — at this level, the system selects the best option to implement and carry out that action, based upon a list of alternatives it generates (augmented by alternatives suggested by the human operator). This system, therefore, automates decision-making in addition to the generation of options (as with decision support systems).
9. *Supervisory Control* (SC) — at this level the system generates options, selects the option to implement and carries out that action. The human mainly monitors the system and intervenes if necessary. Intervention places the human in the role of making a different option selection (from those generated by the computer or one generated by the operator), thus, effectively shifting to the decision support LOA. This level is representative of a typical supervisory control system in which human monitoring and intervention, when needed, is expected in conjunction with a highly automated system.
10. *Full Automation*(FA) — at this level, the system carries out all actions. The human is completely out of the control loop and cannot intervene. This level is representative of a fully automated system where human processing is not deemed to be necessary.

3.4 Theories of dynamic task allocation

3.4.1 Cognitive systems engineering

Complex control systems such as aircraft cockpits, air traffic control systems and nuclear power plants are typically composed of highly interrelated combinations of human and automatic controls. Humans and machines must cooperate and collaborate in order to successfully perform the intended actions and achieve the overall goals and objectives of the system. Hollnagel and Woods (1999) have termed these collaborative systems as joint human-machine systems or joint cognitive systems.

When modeling a complex control system involving humans and automation, a number of different models are required. A model is required for human performance, a model is required for the automation, and a model is needed for simulating the physical response of the overall system to the control actions taken by the human and by the automation (Hollnagel & Bye, 2000).

Hollnagel (1999) lists the four conceptual parameters for describing which and how functions may be affected by automation:

1. Amplification — the function may be improved or increased.
2. Delegation —the function is transferred to the automation but remains under control of the human.

3. Substitution or Replacement — complete control for performance of the function is given to the automation.
4. Extension — new functionality is added to the system.

Cognitive systems engineering takes a systems approach with an ecological orientation (R. Amalberti & Sarter, 2000). Cognitive systems engineering emphasizes the holistic study, modeling, and design of the human-machine system as a joint cognitive system rather than studying individual subsystems in isolation.

Hollnagel and Bye (2000) advocate the concept of balanced work as a primary consideration in the design of function allocation. During the performance of a joint cognitive system the resources of the system as a whole are matched to the performance requirements and the human, automation and organizational resources are combined to meet the performance demands. If the performance demands change or resources are added or removed from the system then the system must adjust (re-equilibrate) to current demands and available resources. Reallocation of functions or tasks is one method for reestablishing the equilibrium. However, the reallocation process itself can initiate a destabilization of the current balance of work and require a new equilibrium to be established.

3.4.2 Human centered automation

Human centered design is a process of ensuring that the concerns, values, and perceptions of all stakeholders in a design effort are considered and balanced (Rouse, 1991). Human centered design focuses not only on the user of a product or system but on all the stakeholders involved in the design process.

A human centered approach to the design of automation explicitly considers the impacts of the introduction of the automation on the humans in the system and on the overall behavior of the system at the beginning and continuously throughout the design process. Human centered automation has as its goal to support human efforts rather to replace them.

3.4.3 Ecological/naturalistic design interfaces

Naturalistic decision-making attempts to understand how humans make decisions in real world settings under complex time-constrained conditions. Klein (1991) lists the following features of natural decision making:

1. Ill-defined goals and ill-structured tasks
2. Uncertainty, ambiguity, and missing data
3. Shifting and competing goals
4. Dynamic and continually changing conditions
5. Action-feedback loops (real-time reaction to changed conditions)
6. Time stress
7. High stakes
8. Multiple players

9. Organizational goals and norms
10. Experienced decision makers

As Howard (1999) has noted practitioners do not solve problems; they manage situations. Managing a situation involves making decisions. Experienced decision makers when facing an operational decision rarely use formal analytical methods such as multi-attribute utility analysis or decision analyses since these strategies generally take too long under time constrained conditions. In fact, as Klein (1991) observed these decision makers rarely even consider multiple options, instead choosing a single solution based on past experience. These decision makers then watch the situation evolve and modify or replace the solution if flaws develop.

Orasanu (1993) indicates that Naturalistic Decision Making is schema-based rather than algorithmic. Features of a new situation are assessed and then compared with past situations. A course of action is then determined based on ones that have been found suitable for similar situations in the past. Endsley (1999) notes that when an individual has a well developed mental model of a situation or domain, a direct, single-step link exists between recognized situation classifications (schema) and typical actions that facilitate rapid decision making.

3.4.4 Dynamic cognition

Amalberti (1998) describes a cognitive model for the pilot that he refers to as the dynamic control model of cognition. This model is based on the theory that there is an ongoing balancing of the desire to optimize the attainment of goals and to minimize the cognitive resources required for these efforts. The cognitive resources include perception, action, memory and reasoning capacities. Meta-cognitive knowledge is employed to seek solutions that limit the demands on the resources. Under abnormal, time-critical conditions, fighter pilots have been observed to consider only a few preplanned diagnosis with associated preplanned responses rather than employing additional cognitive resources for a detailed assessment of the situation. Under these conditions they are trading optimal mission performance for a reduction in required cognitive resources. Thus, to limit the cognitive resources expended, the potential risk of failure is accepted (from a sub-optimal or erroneous solution), the situation is simplified, and only a few pre-planned actions are considered.

Pilots use various abstractions to simplify their mental model of the world and current situation. This simplification reduces the cognitive resources required to adapt and control the current situation. This simplification also introduces the risk of erroneous decisions and actions. Preplanning and anticipation of future events reduce uncertainty and allows for proactive actions. Training and rehearsal enhance skills and automatic behaviors that reduce the cognitive resource needs.

3.4.5 Human triggered function allocation

Campbell et al. (1997) argue that when an agent is about to make a decision regarding allocating functions or tasks to another agent an experienced agent would (or should):

1. assess his own state with regard to workload and capability to perform the activity,
2. estimate the cost of allocating the function such as the increase in communications, monitoring and interactions,
3. make a determination regarding the ability of the second agent to perform the activity, and
4. make judgments regarding the trust and confidence he has in the agent successfully performing the activity.

Campbell has termed items 1 and 2 meta-cognitive processes and items 3 and 4 organizational (or social) cognitive processes. Table 4 summarizes the research issues associated with each process.

3.4.6 System triggered function allocation (adaptive automation)

Campbell describes two concepts for function allocation that are initiated by the automation itself: measure-based and model-based.

Measure-based system-triggered function reallocation seeks to make automated decisions regarding function or task reallocation based on some set of empirical criteria related to the human s situational state and judgments regarding the human agents current performance capabilities. Metrics considered in past studies have included psychometric and physiological parameters such as EKG, heart rate, and eye movement to ascertain workload level and human affective state.

Campbell notes that it is not generally sufficient to base function reallocation decisions solely on an assessment of workload change. Other measures of situational and agent state may be required to support system-triggered dynamic function allocation.

Campbell also describes a model-based approach to system-triggered function relocation. This approach envisions the use of human performance models (e.g., ACT-R, Soar) that are running in real time to monitor and predict the human situational state and trigger function reallocation based on predefined thresholds. Although this is an interesting concept, Campbell argues that the current human performance models are not sufficiently robust to support this type of activity and that measure based triggers can be validated more directly, since unlike human performance models the human state metrics are visible.

Table 4. Research Issues by Basic Process and Application Focus (Campbell et al., 1997).

Category	Specific process	Training issues	Work/ workstation design issues	Automation design issues
Meta-cognitive Processes	¥ First agent assesses own internal state.	¥ How to train people to make more stable and reliable judgments on their own ability to handle (additional) tasks at present and future state?	¥ Designing ways to allow a person to visualize or assess their own future as well as current workload, information flow, etc.	¥ How to give automation systems the ability to estimate their own capacity to take on additional tasks in a given situation?
	¥ First agent assesses the cost of allocation.	¥ How to train people to better anticipate the consequences (communications, key-strokes, etc.) that might be necessary to support, or result from, a function allocation?	¥ Designing a workstation to minimize or automate the communication requirements for functions that may be dynamically shared.	¥ How to give the automation system the ability to tell the person what information, etc. it will need if and when it is given a specific task in a specific DFA setting?
Organiz-ational Cognitive Processes	¥ First agent assesses the second agent s ability.	¥ How to train people to develop better mental models of the situational abilities and reliabilities of the human and/or automated agents to whom functions might be dynamically allocated?	¥ Creating DFA interfaces that can represent or visualize attributes of task requirements and automation system capabilities to aid human first agent in matching second agent capabilities with local task requirements.	¥ What kind of information could an automation system provide on its abilities, past behavior, etc. that could help a human decide on whether it was feasible to allocate a given function to that automation system in a given DFA situation? ¥ How to build the capability to provide that information into the system?
	¥ First agent determines its confidence in the second agent.	¥ How to train people to better judge the situational reliabilities of the human and/or automated agents to whom functions might be dynamically allocated?	¥ Designing DFA interfaces that allow dynamically allocated functions to be tracked by first agent and easily recalled if quality degrades.	¥ What kind of information could an automation system provide on the likely quality of its results to help a human evaluate its reliability in a given DFA situation? ¥ How to build the capability to provide that information into the system?

Suchman (1987) in her famous study pointed out that there are deep asymmetries between what the human perceives of the context of an interaction and what the machine can perceive. Her observations indicated that another human observing the human operator of a machine can often readily perceive what the difficulties are and intervene to assist the operator. However, the machine has only limited knowledge of the observable actions of the user that result from the user s actions that directly affected the machine s own state. With this limited knowledge of the user s actions combined with a pre-determined limited set of response actions the machine may not respond in a manner that the user expects that it should. Without a rich shared knowledge of the interaction, communications between the user and machine become problematic.

Several recent researchers have been investigating methods for automation to increase its contextual and situational awareness without imposing additional burdens on the human operator. Onken (1997) indicates that the automation should have available the same aspects of the contextual situation as the human crew. It would be desirable if the automation had an even more comprehensive view. His view is that the automation should evolve into a fully situational aware team player that can monitor the human crew s activities and other contextual factors, provide recommendation and guidance to the crew members and perform functions as needed under direction of the crew.

Onkin has developed the CASSY intelligent cockpit assistant with the goal to incorporate cognitive systems in the cockpit, which are capable of processing abstract human-like knowledge

- to independently assess necessary situation-relevant information about mission goals, aircraft environment, aircraft systems and aircrew,
- to understand the flight situation,
- to independently interpret the flight situation in the light of the goals of the flight mission,
- to support necessary replanning and decision making,
- to know which information the crew needs,
- to detect pilots' intents and possible errors, and
- to introduce human-like communication initiatives by the cockpit systems .

Andes (2001) describes the intelligent Cockpit Intent Estimator (CIE) system for the Rotorcraft Pilot s Associate (RPA). The RPA acts as a decision aiding entity aware of mission objectives, knows how to execute tasks, and will flexibly and dynamically aid the crew in support of the mission objectives. The RPA is intended to be a virtual co-pilot in advanced Army rotorcraft. The CIE is a component of the RPA s cockpit interface, known as the Cockpit Information Manager (CIM) function. The main purpose of the CIE is to interpret the intent of the flight crew through observation of the activities and actions of the crew and without explicitly and repeatedly querying the crew members. Andes defines intent interpretation as the process of identifying patterns of human operator behavior in order to form a causal explanation for observed actions in terms of the current objectives of the operator. The CIE monitors the activities of the crew through switch activations, stick and collective movements, sensor usage, etc. Using this objective information and knowledge of mission goals and plans, current understanding of intentions, knowledge of the external world acquired through aircraft sensors, and knowledge of acceptable cockpit behavior the CIE infers the intentions of the flight crew. Another function of the CIE is to identify conflicts between the flight crew s intentions and the RPA.

Zhang and Hill (2000) are performing studies to develop models of virtual humans in synthetic environments for military mission rehearsal and tactics evaluation. They believe that one of the most important attributes of virtual humans is the ability to develop an awareness of the current situations (environment, context). Situation awareness is critical for rational virtual humans in that it supports:

- determination of achievable goals,
- selection of appropriate strategies and tactics,
- determination of a course of actions,
- prediction of possible reactions and consequences,
- establishment of focused attention,
- intelligent allocation of limited resources,
- explanation of decisions made, and
- reduction in uncertainty and a speed up of reasoning processes.

They identify two elements that are necessary for development of situation awareness in virtual humans. The first element is a representation of the situation that includes information about the relevant objects, their features and logical, organizational and spatial relationships, actions for supporting understanding the situation, and possible actions for responding to different perceptual input and external events. They call this representation a *situation template* or *template* for awareness. The second element is a set of tools for situation assessment that support: identification of the relevant objects in a visual field from perceptual inputs, finding association relationships among the perceived objects and creation of a structured representation of the objects, and mapping the structured representation to possible situation templates and identification of the most similar ones. They call the structured representation of a set of sensed objects a *pattern.*

The situation assessment model that they have implemented is a combination of the descriptive(system architecture based on Endsley s model — see Section 3.3.5) and prescriptive (production rules) approaches. Their initial efforts have been directed at using situation awareness as the interface between perception and cognition by directing the focus of attention. Without a focus of attention the perceptual system of virtual humans can be overloaded by the volume of information to be processed in the synthetic environment.

3.4.7 Contextual control model (COCOM)

The contextual control model (COCOM) is described as a functional control model and is differentiated from structural models of human cognition based on the human information processor metaphor (Hollnagel, 2000). The current version of COCOM requires three parameters to describe the control of human performance; number of goals, subjective available time, and the current control mode, and two functions; choice of next action, and evaluation of outcomes.

The number of goals is the internal representation of the mental workload that the human experiences in a situation. Its corresponding external parameter is the number of tasks to be performed to achieve these goals. The subjective available time represents the humans perception of the available time to perform an action or complete a task. The current control mode represents the characteristics of the humans performance given the situational context, the humans knowledge and experience and the humans expectations regarding how the situation may evolve. Hollnagel (2000) has identified four overlapping control modes with the following characteristics:

1. Scrambled control mode — The choice of next action is random or irrational, there is little cognition and performance is essentially by trial and error.
2. Opportunistic control mode — The next action is guided by what the human perceives as the important aspects of the current situation, there is little planning or anticipation involved.
3. Tactical control mode — Performance follows a known procedure or rule, there is some anticipation of how the situation may develop, planning is of limited scope and range.
4. Strategic control mode — The human looks ahead at higher level goals, performance is guided less by the current situation and more by the perception of how the situation will evolve and how this will impact the goals.

The choice of next action is a function that evaluates the next action performed based on the current control mode. In each control mode the human s constructs (assumptions and knowledge) and competences (actions, plans and template) are used to different degrees. In the scrambled control mode the choice of next action is determined by the need to meet the single immediate dominant goal. In the opportunistic control mode it is also determined by the need to meet the immediate dominant goal. However, some consideration is given to whether the action is possible given the situation and several goals may be considered, but not coincidental in a systematic or integrated manner. In the tactical control mode the choice of next action is extended to look at the preconditions for the action and the interactions with other goals. Extensive use is made of known plans and procedures and the results of past actions and the expected results of the current action are considered. In the strategic control mode the characteristics of the tactical control mode are extended to include an assessment of the present and future conflicts between goals and plans and procedures are used extensively and may be developed or modified based on the situation.

The evaluation of outcome function also differs among the control modes. In the scrambled control mode the evaluation is as simple as possible; did the action result in the goal being achieved? In the opportunistic control mode the evaluation considers both whether the primary goal was achieved and whether the outcome was that which was expected. In the tactical control mode the evaluation of possibly complicating factors will also be considered (side effects) and indirect indications of the outcome. In the strategic control mode short and long term consequences of actions are considered and the impact of the outcome on all the goals is assessed.A summary of the characteristics of the control modes is shown in Table 5.

Table 5. Main Characteristics of the Control Modes from Hollnagel (2000).

	Scrambled	Opportunistic	Tactical	Strategic
Number of Goals	One	One or two (competing)	Several (limited)	Several
Subjectively Available Time	Inadequate	Just Adequate	Adequate	Adequate
Choice of Next Action	Random	Association based	Plan based	Prediction based
Evaluation of Outcome	Rudimentary	Concrete	Normal	Elaborate

3.4.8 Modeling situation awareness and pilot state

Mulgund (1997) describe research conducted to assess the feasibility of an adaptive pilot/vehicle interface (PVI) that uses pilot mental state metrics (workload, information processing burden, engagement level) and on-line situation assessment models to adaptively determine the content, format, and modality of cockpit displays. The pilot workload is inferred using a belief network approach from pilot physiological measurements including heart rate, heart rate variability, blink rate, blink duration, respiration rate, and EEG. The situation assessment model uses the aircraft sensor outputs and a belief network model to assess the threat level. The adaptation module dynamically changes the cockpit displays based on the assessed workload and threat level. The level of automatic interface adaptation was assessed using a variation of Sheridan s 10 level scale of automation (section 2.6).

4 Data on Dynamic Task Allocation

In order to know how best to allocate tasks to users, we will need to know the advantages and disadvantages of the various possible strategies of allocating tasks. This knowledge will require observing users doing a range of tasks with a range of ways of task allocation.

We present here a few representative studies that illustrate user's behavior where the task allocation algorithm is static, and a few studies were the allocation is done in a dynamic manner. These studies indicate a complex interaction between the tasks, user's expertise and abilities, and the allocation algorithm.

4.1 Static allocation studies

How do people perform tasks when the tasks are passed to them by automation in a static way, that is, at specific times and in specific ways? We note here a few representative studies that examine how users perform these tasks when interrupted by a fixed type of automation in specific ways. These levels of automation can be viewed as a type of interruption, in that tasks and their control are passed to the operator from the automation.

Additional studies are available on how users perform secondary tasks without automation. These can be viewed as studies into self-generated interruptions. As such, their results can be compared with automation doing the task allocation in either a fixed, static way, or in a dynamic way.

Bailey and Konstan (2001) examined the effect of interrupting a user as they performed six different types of simple tasks, such as adding numbers and reading a short paragraph. The users were interrupted either at the end of tasks or in the middle of tasks to perform a simple secondary task. Time to perform each task, and users' annoyance and rating of difficulty of each task were measured.

There were several interesting findings. Users performed the primary task more slowly when they were interrupted in the middle of the task, even when the time on the secondary task is removed. The interruptions in the midst of performing a task were particularly annoying and caused more anxiety. Finally, interruptions made the task seem more difficult.

These results suggest that users can switch from a primary task to (the beginning of) a secondary task easily, but they have trouble switching back to the middle of a primary task. This is consistent with the theory of Altmann and Trafton (2002), that interruptions at the end of goals are more easily managed than interruptions that force the primary task goals to remembered.

McFarlane (1998; 1999) suggested four types of interruptions strategies. These strategies can be seen as a type of task allocation communication mechanism. These include (a) immediately interrupting the user, (b) negotiating an interruption, that is, let the user know an interruption is pending and letting them choose the time to respond, (c) mediated, where the interrupter takes some account of the user's activities and chooses a better time for interruptions, and (d) batched, where a set of interruptions during a given time period are dealt with all at once.

McFarlane ran a study comparing the four interruption approaches, which can be viewed as examining four ways of task allocation. The primary task was a computer game-type task that required multiple real-time steps for success. In this case, the automation was handing tasks to the user to do. The tasks handed out by the automation were a matching test similar to the Stroop task (when in a word naming task the stimuli color and word are sometimes mismatched, leading to errors based on naming the color or the word instead of vice versa). Users did not automate the second task even after two hours of practice.

The results indicated that the different strategies lead to reliably different performance on a variety of measures, and that no strategy was best across all measures. For example, negotiated interruptions lead to the best performance on the main task, but the worst performance on the secondary task.

Ruff, Narayanan, and Draper (accepted pending revisions) examined how fixed levels of automation influenced performance on a remotely operated vehicle (ROV) task. They showed that automation that interacted with the user (management by consent) led to better performance than management by exception or a completely manual mode. While these results might be specific to the task and the automation, their results suggest that automation that works with the user and that allows the user more control leads to better performance in a variety of measures, including raw task performance, self-ratings of situation awareness, and trust in the system.

4.2 Dynamic allocation studies

Endsley and Kabor (1999) performed a series of experiments to assess the impact of intermediate levels of automation (see section 3.3.5 for a discussion of the levels of automation proposed by Endsley) on human-system performance, operator situational awareness, and workload for a complex dynamic control task. The impact of automation level on the capability of the human operator to assume manual control following automation failure was also investigated.

Endsley and Kabor s experimental results suggest that LOAs that involve sharing option generation and implementation between human and machine have a significant impact on system performance. These experiments revealed that humans benefited most from task implementation assistance (either computer aided implementation assistance or complete implementation assumption by the computer) and were somewhat negatively affected by automated assistance for higher level cognitive functions such as decision-making and option generation. LOAs that involve human generation of options with computer implementation were found to produce superior results during normal operations. Joint human-machine option generation (decision-making) degraded performance compared with option generation by either the human or machine acting alone.

Their results also indicated that operator ability to recover from a automation failures is significantly better with LOAs that require some operator interaction in the implementation role. Implementation strategies that involve the automation providing assistance with the manual workload (but still keeping the operator involved in the implementation) associated with the task appeared to be optimal. Surprisingly, little impact on perceived workload of different LOA was noted across the ten LOAs. This result is in contrast to the results or prior studies and could possibly be attributed to the short time duration of the experimental task or that only a single task was performed as opposed to multiple concurrent tasks (Mica R. Endsley & Kaber, 1999).

The CASSY intelligent cockpit assistant described in Section 3.4.6.3 was subjected to in-flight experiments in a real world aviation environment (Onken, 1997). The system was tested in the experimental cockpit of the Advanced Technologies Testing Aircraft System (ATTAS) which is a specially developed modification of a 44-seat commuter jet and 10 typical IFR regional flights in high traffic areas were performed. The experimental cockpit was a designed as a standard modern flight deck with airbus displays and autopilot. The CASSY system was been integrated into the experimental cockpit in the ATTAS.

The CASSY flight tests demonstrated that intelligent cognitive systems based automation can be integrated into the cockpit of modern aircraft. Simulator and aircraft flight tests of the system indicated an increase in the joint system (human-machine) situation assessment. The situation assessment capability dissimilarities between the pilots and CASSY cognitive assistant led to complimentary performance. This elevation of joint situation assessment was similar to that resulting from a human flight crew (pilot-flying and pilot-not-flying) where each crew member examines the situation in a dissimilar manner based on their current role. The tests indicated that the dissimilarities in situation awareness of the human and an intelligent automated cockpit assistant resulted in a reduction in the number of undetected errors, whether these errors were committed by the pilot or by the automation. The tests also demonstrated the potential capabilities of automated features such as pilot intent recognition and complex flight planning.

In another study, Scallen and Hancock (2001) found that in a multi-tasking situation, automating one task as another task was introduced not only provided improved performance during the automation for both tasks but also had carryover effects. Performance measured as deviation from an ideal on a tracking task was about 10% better when the automation was not active. They hypothesized that this improvement was due to reduced operator fatigue.

Harris et al (1995) found benefits when allowing users to choose when to switch between manual and automatic modes. Users' performance was better than when the task was all manual, or all automatic if they had practice with the automation. Their results suggest that it may be better to allow users to do the dynamic task allocation, and that practice with the automation will be required before optimal performance results.

4.3 Summary

The studies on how users work together with various types of automation that helps allocate tasks suggests several comments. The first is that we will have to look at usability after practice and training, both of which could make an initially awkward system the most powerful. While the McFarlane study examined learning, enough to show that one of the tasks was not automated, we know that learning and training are important in dual-tasks (Chong & Laird, 1997; Wickens & Hollands, 2000).

The second is that having users allocating the tasks instead of the automation allocating the tasks might be the best approach. Studies, such as Ruff, et al., show that control with human input perform better. Further work should look at having users self-schedule or having them choose their own strategy for interruption.

The third is that we will need more data to understand particular tasks. This data will have to include performance data, not just on what people would like, or feelings after having used a system, but direct performance measures. We may find that in this area, like so many others, that performance is not correlated with perceived effort (e.g. Dawes, 1994; Ericsson & Simon, 1993; Hancock, Williams, & Manning, 1995).

The final is when and how to best share tasks appears to depend on many factors. McFarlane (1998; 1999) found that different strategies lead to different performance on a variety of metrics, with no strategy dominating on all metrics. This may be because we have not fully grasped the theoretical types of interruptions suggested by McFarlane, or have not created cognitive models of the user being interrupted as provided by Altmann and Trafton (2002). Future work, if it wants to predict the impact of task allocation and task allocation strategies on performance, will need to do more detailed theoretical analysis.

5 Recommendations for Improving Pilot/Automation through Dynamic Task Allocation

<u>Avoid providing multiple options</u> — A number of research studies have pointed out that human decision-making in real-world time constrained or resource constrained settings does not follow a model of a formal decision making process. Instead, humans when faced with making a decision under these conditions attempt to match the current situation with an existing schema based on their personal experience and training and effect the actions that have been successful in the past. This model of human decision-making argues against (the automation) providing multiple options to the human for consideration. Rather, the automation should monitor the actions of the human and only intervene if it appears that these actions are seriously detrimental to goal achievement.

<u>Minimize impact of interruptions</u> — Interrupting humans when performing critical tasks, particularly under time-constrained conditions, can lead to serious mistakes. The intelligent agent should have an awareness of the context and the shared environment including an understanding of what task the human is currently engaged in, how critical this task is and how important the interruption (at this particular time) is relative to this task.. The agent should use this awareness as well as what is known about interruptions to chooses appropriate times to intersect with the human.

<u>The human should be an active participant rather than a passive monitor</u> — Assigning humans the function of monitoring the performance of automation has been identified as a major weakness in current automation design. Humans are ill-suited at monitoring the performance of highly reliable systems. The reduction of the role for the human operator to that of a monitor has been associated with a number of negative factors including reduction in vigilance, complacency, loss of skills, loss of situational

awareness, and skill decays. The human operator needs to be meaningfully involved at a high (cognitive) level in all significant system tasks.

Humans have responsibility and must be given control authority — A central concept is that the human(s) in the system have the ultimate responsibility for the performance of the system and must be given control authority. Consequently, they must be supplied not only with sufficient information to evaluate the situation but mechanisms to affect the control of the system. For situations involving human-machine systems with the capability for automation initiated dynamic task allocation the human must be informed of the intentions of the automation to assume control of the performance of some task. Furthermore, the human must be able to either reject this intention, to query the machine agent as to the reasons for this action and/or to modify the intended actions of the automation. This can be accomplished, for example, by allowing the automation to assume only a subset of the intended tasks/functions.

The automation should clearly indicate its behavior and state — The ability for the human elements in a human-machine system to develop and maintain situational awareness during all phases of system operation is critical to safe and efficient system operation. A number of attributes of the joint system that support situational awareness in the human are:

- An understanding of what the current states of the other team members (including automation) are in terms of their goals, intentions and future actions.
- An awareness of the environment, context and system state.

The automation must be capable of inferring the human and environment context and state — In order for the automation to function as an effective member of human-machine team it must be capable of developing and maintaining an appropriate internal model of the shared environment and context, the goals and the current intentions and actions of the other team members including humans. It must be capable of developing and maintaining this knowledge through appropriate sensing and integration of available system and environmental parameters and without requiring explicit instructions or explanations from the other team members. In short, the automation must have the capability for developing a situational awareness that will compliment the other team members and will facilitate communication, coordination and development of a shared understanding.

A potentially key component of situational awareness is for the team members (including automation) to have an understanding of the current affective and physical state of the humans. Research has shown that affective state can have a profound influence on human cognitive processes, performance and potential for error. While it appears possible to measure certain parameters and from these measurements infer the human s affective state (at least in a relative sense), it is not clear from the research what specific actions could (and should) be taken by the automation in response to sensed changes in the human affective state. This area requires further research.

Intermediate levels of automation may be optimal - Recent research suggests that there is a benefit to human-machine joint system performance from intermediate levels of automation. The largest benefits come from task implementation assistance and performance is negatively affected by automated assistance for higher level cognitive functions such as decision-making.

Automation should provide a varied, but not too varied, set of tasks to the user. Vigilance tasks and long times on a given task are associated with poorer performance on a variety of measures (for a review, see (Wickens & Hollands, 2000). Providing pilots with breaks through automation can improve their performance as long as the cycle time (automation or human as controller) is not too short (Scallen & Hancock, 2001; Scallen, Hancock, & Duley, 1995).

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