Human Factors and Ergonomics in Automation Design

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CHAPTER 59

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1 INTRODUCTION

Automation has a long history marked by many successes and equally notable failures. In the early nineteenth century the Luddites in northern England protested against the introduction of automation in the weaving industry by sabotaging the machines. Although the term *luddite* now refers to technophobes, these people correctly foresaw some of the highly damaging changes that automation would bring to their lives. Automation and the industrial revolution radically changed the craft-centered culture of the time. More recently, information technology has had an equally important effect on industries as diverse as process control, aviation, and ship navigation.

The Luddites foresaw the threat to their lifestyle. Of greater concern are situations in which people fail to recognize the risks of adopting automation and are surprised by unanticipated effects (Sarter et al., 1997). Automation frequently surprises designers, operators, and managers with unforeseen mishaps. As an example, the cruise ship *Royal Majesty* ran aground because the global positioning system (GPS) signal was lost and the position estimation reverted to position extrapolation based on speed and heading (dead reckoning). For over 24 h, the crew followed the compelling electronic chart display and did not notice that the GPS signal had been lost or that the position error had been accumulating. The crew failed to heed indications from boats in the area, lights on the shore, and even salient changes in water color that signal shoals. The surprise of the GPS failure was discovered only when the ship ran aground [National Transportation Safety Board (NTSB), 1997; Lutzhoft and Dekker, 2002]. This mishap demonstrates the power of technology to either make us smart or surprisingly stupid (Norman, 1993). Automation exemplifies this power.

Automation has been defined as a device or system that performs a function previously performed by a human operator (Parasuraman et al., 2000). However, automation does not simply supplant the person, but enables new activities, creates new roles for the person, and changes existing activities in unexpected ways (Woods, 1994). As a result, automation often produces surprises at many levels, from the societal, as with the

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Luddites, to the individual, as with the *Royal Majesty*. For automation to achieve its intended benefits, its design must anticipate these changes. The need to anticipate and avert automation-related surprises is more difficult now than ever. One of the ironies in automation design is that as automation increasingly supplants human control, it becomes increasingly important for designers to consider the contribution of the human operator (Bainbridge, 1983). This chapter draws upon over 30 years of research to identify general automation-related failures and to identify strategies for improving automation design.

2 AUTOMATION PROMISES AND PITFALLS

Automation has many clear benefits. In the case of the control of cargo ships and oil tankers, it has made it possible to operate a vessel with as few as 8–12 crew members compared to the 30–40 that were required 40 years ago (Grabowski and Hendrick, 1993). In the case of aviation, automation has reduced flight times and increased fuel efficiency (Nagel, 1988). Similarly, automation in the form of decision support systems has been credited with saving millions of dollars in guiding policy and production decisions (Singh and Singh, 1997). Automation promises greater efficiency, lower workload, and fewer human errors; however, these promises are not always fulfilled.

Many pitfalls plague the introduction of automation. Well-documented failures of information technology show that it seldom provides the promised economic benefits (Landauer, 1995) and often fails to provide promised safety benefits (Perrow, 1984). When automation is introduced to eliminate human error, the result is sometimes new and often more catastrophic errors (Sarter and Woods, 1995). Automation often fails to provide expected benefits because it does not simply replace the human in performing a task but also transforms the job and introduces new tasks. These new tasks are not always recognized and so designers fail to provide operators with adequate feedback and support. Automation also fails because the role of the person performing the task is often underestimated, particularly the ability to compensate for the unexpected, and that role is not supported. Although any list of automation-related problems and surprises will be incomplete, changes in feedback, task structure, and relationships represent critical challenges of automation design (Lee and Seppelt, 2009).

Feedback changes:

- Out-of-the-loop unfamiliarity
- Surprising mode transitions
- Inadequate training and skill loss

Task structure changes:

- Clumsy automation
- Automation task errors
- Behavioral adaptation

Relationships change:

- Mismatched expectations and eutactic behavior
- Inappropriate trust (misuse, disuse, and complacency)
- Job satisfaction and health

2.1 Feedback Changes

Automation often fails because it dramatically changes the feedback the operator receives. Diminished or eliminated feedback is a common occurrence with automation and it can leave people less prepared to detect automation failures or to intervene.

Out-of-the-loop unfamiliarity refers to the diminished ability of people to detect automation failures and to resume manual control (Endsley and Kiris, 1995). Several factors underlie this problem. First, automation might reduce feedback, and the remaining feedback may be qualitatively different than that received when operating under manual control (McFadden et al., 2003). With manual control operators often have both proprioceptive and visual cues, whereas under automatic control they may have only visual cues (Wickens and Kessel, 1981). Automation also reduces feedback because it distances operators from the process. Introducing automation into papermaking plants eliminated the informal feedback associated with vibrations, sounds, and smells that many operators relied upon (Zuboff, 1988). Second, monitoring the performance of automation involves passive observation of changes in system state, which is qualitatively different than the active monitoring associated with manual control (Gibson, 1962; Eprath and Young, 1981). In manual control, perception actively supports control, and control actions guide perception (Flach and Jagacinski, 2002). Monitoring automatic control disrupts this process. Third, automatic control can induce the operator to disengage and direct attention to other activities, further compromising the feedback from the system. The tendency to rely complacently on automation, particularly during multitask situations, may reflect this tendency to disengage from the monitoring task (Parasuraman et al., 1993, 1994; Metzger and Parasuraman, 2001). Finally, the operator's mental model may be inadequate to guide expectations and control. In particular, the automation may use control algorithms that are at odds with the control strategies and mental model of the person, making it difficult to anticipate the actions and limits of the automation (Goodrich and Boer, 2003). Operators with substantial previous experience and well-developed mental models detect disturbances more rapidly than operators without this experience, but extended periods of monitoring automatic control may undermine this skill and diminish operators' ability to generate expectations of correct behavior (Wickens and Kessel, 1981). This skill loss may also undermine operators' self-confidence, which can make them less inclined to intervene (Lee and Moray, 1994). Overall, out-of-the-loop unfamiliarity stems from disrupted feedback that diminishes the ability to form correct expectations, detect anomolies, and control the system manually.

An example of out-of-the-loop unfamiliarity occurs in driving. Adaptive cruise control (ACC) has the potential to induce out-of-the-loop unfamiliarity, leading to delayed and less effective braking responses in situations in which the ACC is not able to respond to a braking lead vehicle (Stanton and Young, 1998). ACC uses sensors to maintain not only a set speed, as with conventional cruise control, but also a set distance to cars ahead. When drivers engage ACC, they no longer receive the haptic feedback that conveys the degree of braking needed to slow the vehicle in response to the braking behavior of vehicles ahead. Drivers also revert to passive monitoring of other vehicles rather than directing their attention toward the active control of their headway. Most important, ACC may induce drivers to direct their attention to nondriving activities such as cell phone conversations or reading the newspaper (Ward, 2000). Such distractions clearly delay driver response (Lee and Strayer, 2004). More subtly, drivers may have a poor mental model of the ACC control algorithms and so may not be able to anticipate situations that lie beyond the capabilities of the automation.

The difficulty of anticipating the behavior of the automation has also been seen in aviation, in which verbal protocol data show that pilots have problems with automation because of poor feedback and difficulties developing expectations regarding the behavior of the automation (Olson and Sarter, 2001). Analysis of eye movements, mental model probes, and pilot behavior showed that inadequate feedback and the associated poor monitoring are major contributors to automation mishaps (Sarter et al., 2007).

Mode errors often result from poor monitoring associated with poor feedback (Woods, 1994; Sarter and Woods, 1995). These arise when operators fail to detect the mode or recognize the consequence of mode transitions in complex automation. Substantial research with cockpit automation demonstrates that flight management systems often surprise pilots with unexpected mode transitions. These complex systems use a combination of the pilots' commands and system coupling to transition between modes. Mode transitions are often not commanded explicitly by the pilot and sometimes go unnoticed (Sarter and Woods, 1995).

Electronic charts in maritime navigation also offer the potential for mode errors. Such charts have several modes for determining a ship's position. One uses GPS data, another uses position extrapolation based on speed and heading (dead reckoning) to estimate the ship's position. If the GPS signal is lost, the electronic chart system changes automatically to the dead reckoning mode. This mode transition is signaled by a short alarm. If the alarm is not detected, however, the mariner may not notice that the GPS signal is no longer the basis for position estimates. Furthermore, many electronic charts do not maintain a continuous visual record of the vessel track. A track line is shown as long as the same chart or scale is used, but if the scale is changed, the track line is lost. The lack of track line continuity further undermines the ability of mariners to detect a transition from GPS to dead reckoning position estimates. If the mariner does not notice this mode transition, the ship can drift many miles from the intended course while the electronic chart continues to display the position as if the vessel were following that course precisely. This is exactly what happened in the grounding of the cruise ship *Royal Majesty*, where the GPS signal was lost and the position estimation transitioned to the dead reckoning mode. The mode transition was noticed only when the ship ran aground (NTSB, 1997).

Skill loss refers to automation that leaves the operator without the appropriate skills to accommodate the demands of the job. In situations in which the automation takes on the tasks previously assigned to the operator, the skills of the operator may atrophy as they go unexercised (Endsley and Kiris, 1995). Part of this skill loss reflects diminished feedback. This is a particular concern in aviation, where pilots' aircraft handling skills may degrade when they rely on the autopilot. In response, some pilots disengage the autopilot and fly the aircraft manually to maintain their skills (Billings, 1997).

2.2 Task Structure Changes

Clumsy automation refers to the situation in which automation makes easy tasks easier and hard tasks harder (Wiener, 1989). As Bainbridge (1983) notes, designers often leave the operator with the most difficult tasks—those designers are unable to automate. Because the easy tasks have been automated, the operator has less experience and an impoverished context for responding to the difficult tasks, as a result of the out-of-the-loop problem mentioned above. In this situation, automation has the effect of both reducing workload during already low-workload periods and increasing it during high-workload periods. For example, a flight management system tends to make the low-workload phases of flight (such as straight and level flight or a routine climb) easier but high-workload phases (such as the maneuvers in preparation for landing) more difficult, as pilots have to share their time between landing procedures, communication, and programming the flight management system. Such effects are seen not only in aviation but also in the operating room (Cook et al., 1990b; Woods et al., 1991). The unfortunate tendency of operators to more willingly delegate tasks to automation during periods of low workload, compared to situations of high workload (Bainbridge, 1983), increases the prevalence of clumsy automation. This observation demonstrates that clumsy automation is not simply a technical problem, but one that depends on operator attitudes such as trust (Lee and See, 2004; Madhavan and Wiegmann, 2007).

The burden of clumsy automation is more prevelant than reported because operators adapt to clumsy automation, either tailoring their tasks or configuring the automation to adapt to poorly designed automation (Cook et al., 1990a). These strategies can mask the effects of clumsy automation in routine situations and make it appear more effective than it really is. When operators encounter abnormal situations, the problems of clumsy automation may emerge unexpectedly.

An example of potentially clumsy automation in maritime navigation occurs when the GPS is integrated with digital charts to create electronic chart display and information systems (ECDISs). When combined with existing advanced maritime navigation systems (e.g., automatic radar plotting aid), these technological innovations tend to reduce repetitive physical activity while potentially increasing the mental demands made on the crew. The reduction in physical demands implies the possibility of reducing the number of personnel required on the bridge from as many as four people (captain, watch officer, helmsman, and lookout) to one. Recent studies suggest that under proper conditions workload declines and performance rises with one-person operations (Schuffel et al., 1988); however, this research has addressed only routine performance and has not considered more stressful conditions. Software failures and dense traffic situations combine to increase the workload substantially relative to the traditional system (Lee and Sanquist, 1996). This finding is consistent with poorly designed automation in the aviation and operating room, which reduces workload under routine conditions but increases it during stressful conditions (Wiener, 1989; Woods, 1991).

Clumsy automation can occur at the individual and organizational levels. Automation promises to reduce the need for human labor; during routine circumstances, fewer people are able to control the system effectively. The dramatic reduction in crew members needed to operate large ships testifies to this fact. However, clumsy automation at the macrolevel can occur when abnormal situations or high-tempo operations challenge the resources of the diminished crew (Lee and Morgan, 1994). Frequently, the wider effects of automation on training and recruitment go unexamined (Strain and Eason, 2000). Clumsy automation at the microlevel of the operator and the macrolevel of the organization represent critical challenges in anticipating the effect of automation.

Automation–task errors refer to the new forms of human error associated with new tasks generated by the introduction of automation. Managers and system designers often introduce automation to eliminate human error. Ironically, new and more disastrous errors can sometimes result. Automation often extends the scope of human actions and delays feedback associated with those actions. As a consequence, human errors may be more likely to go undetected and do more damage.

New automation-related tasks imply new skills are needed. Sophisticated automation eliminates many physical tasks and leaves complex cognitive tasks that may appear superficially easy, leading to less emphasis on training and a poor understanding of the automation. On ships, misunderstanding of new radar and collision avoidance systems has contributed to accidents (NTSB, 1990). One contribution to such accidents is training and certification that fail to reflect the demands of the automation. An analysis of the exam used by the U.S. Coast Guard to certify radar operators indicated that 75% of the items assess skills that have been automated and are not required by the new technology (Lee and Sanquist, 2000). The new technology makes it possible to monitor a greater number of ships, enhancing the need for interpretive skills such as understanding the rules of the road and the automation. These are the very skills that are underrepresented on the Coast Guard exam. While increasing automation might relieve the operator of some tasks, they are likely to create new and more complex tasks that require more, not less, training.

Brittle failures are typical of human–automation interactions in which novel problems arise or even simple data entry mistakes are made with systems that completely automate the decision process and leave operators to assess the automation's decision (Roth et al., 1987; Roth and Woods, 1988). Such failures contrast with *graceful degradation*, a common characteristic of time-tested manual processes. Brittle failures are characterized by a sudden and dramatic decline in system performance, whereas graceful degradation is characterized by a more gradual and predictable decline. For example, a flight-planning system for pilots can induce dramatically poor decisions because it assumes that weather forecasts represent reality and lacks the flexibility to consider situations in which the actual weather might deviate from the forecast (Smith et al., 1997).

In maritime navigation, electronic charts introduce the potential for brittle failures in position estimation. Electronic charts distance mariners from the process of recording vessel position, leaving them with little insight into the factors that might lead to erroneous position estimates. The manual process of recording a position on a paper chart superimposes at least two position estimates, one based on extrapolation of the previous position and one based on visual bearings or other position information. These complementary position estimates help identify errors in determining position (Hutchins, 1995). Unlike the manual position recording on paper charts, electronic charts show the quality of the position estimation only indirectly, in terms of GPS signal quality; however, many mariners have little understanding of the relevance of these numbers, and gross errors in position can result (Lee and Sanquist, 2000).

Automation-related tasks also introduce the opportunity for *configuration errors*. Many forms of automation involve complex configurations or setups, and mistakes made during this process can later prove disastrous. For example, with electronic charts that aid maritime navigation, it is possible to configure the system to test the actual position automatically against the intended track using a feature in which an acceptable safety margin can be specified. If the ship deviates beyond this distance, an alarm sounds (provided that the feature was engaged and the GPS is functioning normally). Failing to engage this feature could jeopardize ship safety if mariners have come to rely on the automated warning. Also, because any one of several mariners can configure the system, system configuration and behavior can change in unanticipated ways as different mariners enter different safety margins. The danger of an inappropriate or unanticipated chart configuration is not a failure mode associated with paper charts but represents an automation-induced error that can threaten ship safety.

Brittle failures and configuration errors tend to undermine individual reliability and may have even greater detrimental effects on team performance (Skitka et al., 2000b). These automation-related errors may be particularly troublesome if the automation also undermines effective error-correcting strategies such as feedback and redundancies in the multiperson position-fixing process

(Hutchins, 1995). For example, because poor position fixes are visible to all team members, crew members who generate these fixes are corrected quickly. Through configuration errors, automation also creates the potential for one team member to induce errors in other team members. These factors all point toward the need to consider automation-induced errors at the level of the team and at the level of the individual.

Behavioral adaptation refers to the tendency of operators to adapt to the new capabilities of the automation, particularly to change behavior and tasks so that the potential safety benefits of the technology are not realized. Automation intended by designers to enhance safety may instead lead operators to reduce effort and leave safety unaffected or even diminished. Behavioral adaptation occurs at the individual (Wilde, 1988, 1989; Evans, 1991), organizational (Perrow, 1984), and societal levels (Tenner, 1996).

Antilock brake systems (ABSs) for cars show behavioral adaptation. The ABS modulates brake pressure automatically to maintain maximum brake force without skidding. This automation makes it possible for drivers to maintain control in extreme crash avoidance maneuvers, which should enhance safety. However, ABSs have not produced the intended safety benefits, in part because with them drivers tend to drive less conservatively, adopting higher speeds and shorter following distances (Sagberg et al., 1997). Similarly, vision enhancement systems make it possible for drivers to see more at night, potentially enhancing safety; however, drivers tend to adapt to the systems by increasing their speed (Stanton and Pinto, 2000).

Behavioral adaptation can also undermine the benefits of automation if the automation causes a diffusion of responsibility and a tendency to exert less effort when automation is available (Mosier et al., 1998; Skitka et al., 2000a). As a result, people tend to commit more omission errors (failing to detect events not detected by the automation) and more commission errors (concurring incorrectly with erroneous detection of events by the automation) when they work with automation. Automation can lead people to conserve cognitive effort rather than increase detection performance. This effect parallels the adaptation of people when they work in groups. Diffusion of responsibility leads people to perform more poorly when they are part of a group compared to individually (Skitka et al., 1999). A similar phenomenon is seen with decision support automation. People often use decision support systems to reduce effort rather than to enhance decision quality (Todd and Benbasat, 1999, 2000). The strong tendency of people to minimize effort and adapt their behavior to the most salient feedback they receive merits careful consideration in the design and implementation of automation. The effects of behavioral adaptation, particularly the diffusion of responsibilility, suggest automation can change relationships between people, a topic we turn to next.

2.3 Relationships Change

Automation redefines not just tasks but also relationships between co-workers, with management, and between designers and users. Critical to defining these relationships is the degree to which people rely and comply with automation. Often designers and managers expect operators to rely on automation in a way that diverges from how people actually use the automation, or how they need to use the automation to maintain system safety and performance.

Eutactic behavior is behavior that approximates an optimal or satisficing response to the automation (Moray, 2003). As a consequence, eutactic behavior is not an instance of inappropriate reliance on automation but an instance of appropriate reliance that may be inconsistent with the expectations of the designers or managers. Misuse and disuse may sometimes reflect poorly calibrated trust, automation bias, or complacency. However, misuse and disuse may also reflect eutactic behavior and appropriate reliance once the costs and benefits are assessed completely. Automation that is generally reliable should be relied upon, even if it fails periodically, if the costs of a failure are modest, and if it relieves the operator of substantial mental effort. Careful monitoring to catch the periodic failure might not be worth the effort in such a case. What may appear to be complacent behavior may actually be appropriate given the costs of monitoring.

Discriminating between complacency and eutactic behavior requires optimizing a cost function that includes the cost of failing to detect failures *and* the cost of monitoring (Moray, 2003). Overreliance may be appropriate given the cost of monitoring. Similarly, disuse may also be appropriate. The new tasks associated with programming, engaging, monitoring, and disengaging automation can make the burden of managing the automation outweigh its benefit (Kirlik, 1993). In this situation, the aid will go unused by a well-adapted operator (Kirlik, 1993). Such behavior is eutactic and should be expected, but designers might be surprised if they fail to consider the burden of automation-related tasks.

Not all over- and underreliance is appropriate. Often operators respond to automation inappropriately, exhibiting a tendency toward misuse and disuse. *Misuse* refers to the failures that occur when people inadvertently violate critical assumptions and rely on automation inappropriately, whereas *disuse* signifies failures that occur when people reject the capabilities of automation (Parasuraman and Riley, 1997).

Another useful distinction in how operators use automation is that of reliance and compliance (Meyer, 2001). *Reliance* refers to the situation in which the operator does not act because the automation has not issued a warning or seems to be performing adequately. In contrast, *compliance* refers to the situation in which the operator acts in response to a warning or command from the automation. Overreliance results in errors of omission (failing to detect events not detected by the automation), and overcompliance results in errors of commission (concurring incorrectly with erroneous detection of events by the automation; Skitka et al., 2000a). Underreliance and compliance are differentially affected by false alarms and misses. Automation prone to false alarms affects compliance and reliance, but miss-prone automation tends to affect only reliance (Dixon et al., 2007).

The influence of false alarms on reliance and compliance is complicated. Although a high rate of false alarms often induces a cry wolf effect and an associated disuse of automation (Bliss et al., 1995), in some cases, such as air traffic conflict alerting systems, the relatively high rate of false alarms did not lead to disuse (Wickens et al., 2009). One reason for this effect is that false alarms are not a homogeneous class of warnings. Users may view some false alarms as useful and other false alarms might help them understand the system and so do not undermine compliance and reliance (Lees and Lee, 2007).

Misuse and disuse of automation may depend on certain attitudes of users, such as trust and self-confidence (Lee and Moray, 1994; Dzindolet et al., 2001). As an example, the difference in operators' trust in a route planning aid and their self-confidence in their own ability was highly predictive of reliance on the aid (de Vries et al., 2003). Many studies have demonstrated that trust is a meaningful concept to describe human–automation interaction, in both naturalistic settings (Zuboff, 1988) and laboratory settings (Halprin et al., 1973; Lee and Moray, 1992; Muir and Moray, 1996; Lewandowsky et al., 2000). People tend to rely on automation they trust and to reject automation they do not trust. In the context of operator reliance on automation, trust has been defined as an attitude that the automation will help achieve an operator's goals in a situation characterized by uncertainty and vulnerability (Lee and See, 2004).

Inappropriate reliance associated with misuse and disuse depends in part on how well trust matches the true capabilities of the automation. Calibration, resolution, and specificity of trust describe the match between trust and the capabilities of automation. *Calibration* refers to the correspondence between a person's trust in automation and the automation's capabilities (Lee and Moray, 1994; Lee and See, 2004). Definitions of the appropriate calibration of trust parallel those of misuse and disuse in describing appropriate reliance. Overtrust is poor calibration in which trust exceeds system capabilities; with distrust, trust falls short of automation capabilities. Figure 1 shows good calibration as the diagonal line where the level of trust matches automation capabilities. Above this line is overtrust and below is distrust. Overreliance on automation has sometimes been termed *complacency* and can result from trusting the automation more than is warranted.

Resolution refers to how precisely a judgment of trust differentiates levels of automation capability (Cohen et al., 1999). Figure 1 shows that poor resolution occurs when a large range of automation capability maps onto a small range of trust. With low resolution, large changes in automation capability are reflected in small changes in trust. *Specificity* refers to the degree to which trust is associated with a particular component or aspect of the trustee. Functional specificity describes the differentiation of functions, subfunctions, and modes of automation. With high functional specificity, a person's trust reflects capabilities of specific subfunctions and modes. Low functional specificity means that the person's trust reflects the capabilities of the entire system. Specificity can also describe changes in trust as a function of the situation over time. High temporal specificity means that a person's trust reflects moment-to-moment fluctuations in automation capability, whereas low temporal specificity means that the trust reflects only long-term changes in automation capability. Although temporal specificity implies a generic change over time as the person's trust adjusts to failures in the automation,

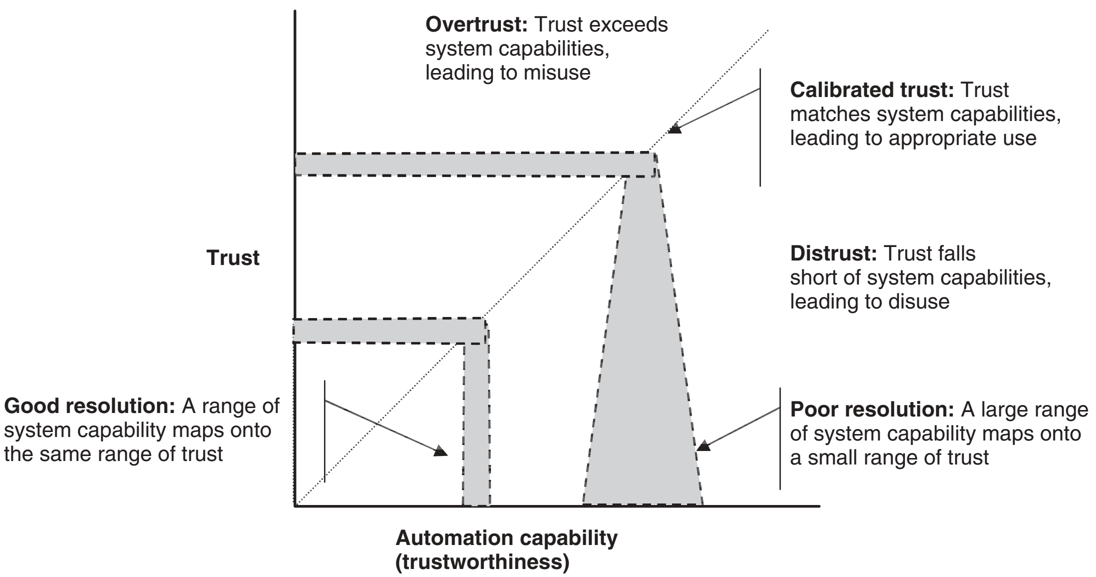


Figure 1 Calibration, resolution, and automation capability define appropriate trust in automation. Overtrust may lead to misuse, and distrust may lead to disuse. (Reprinted with permission from Lee and See, 2004. Copyright 2004 by the Human Factors and Ergonomics Society.)

temporal specificity also addresses adjustments that should occur when the situation or context changes and affects the capability of the automation. High functional and temporal specificity increase the likelihood that the level of trust will match the capabilities of a particular element of the automation at a particular time. Good calibration, high resolution, and high specificity of trust can mitigate misuse and disuse of automation.

The information required to support appropriate trust can be considered in terms of attributional abstraction, which varies from the demonstrations of competence to the intentions of the automation (Lee and See, 2004). A recent review of trust literature concluded that three general levels summarize the bases of trust: ability, integrity, and benevolence (Mayer et al., 1995). Lee and Moray (1992) made similar distinctions in defining the factors that influence trust in automation and identified performance, process, and purpose as the general bases of trust.

Performance refers to the current and historical performance and reliability of the automation. Performance information describes *what* the automation does. More specifically, performance refers to the competency or expertise of the system, as demonstrated by its ability to achieve the operator's goals. Because performance is linked to the ability to achieve specific goals, it demonstrates the task- and situation-dependent nature of trust. This is similar to Sheridan's (1992) concept of robustness. The operator will tend to trust automation that performs in a manner that reliably achieves his or her goals.

Process is the degree to which the algorithms of the automation are appropriate for the situation and able to achieve the operator's goals. Process information describes *how* the automation operates. In interpersonal relationships, this corresponds to the consistency of actions associated with adherence to a set of acceptable principles (Mayer et al., 1995). Process as a basis for trust reflects a shift away from focus on specific behaviors and toward qualities and traits attributed to the automation. With the process dimension, trust is in the automation and not in the specific actions of the automation. As an example, knowing why automation failed increased trust even when it was not warranted (Dzindolet et al., 2003). In contrast, trust tends to drop with any sign of incompetence of the automation, even if the overall system performance is unaffected (Muir and Moray, 1996). Thus, the process basis of trust relies on dispositional attributions and inferences and is similar to Sheridan's (1992) concept of understandability. The operator will tend to trust the automation if its algorithms can be understood and it seems capable of achieving the operator's goals in the current situation.

Purpose refers to the degree to which the automation is being used within the realm of the designer's intent. It addresses the question of *why* the automation was developed. With interpersonal relationships, this depends on the intentions and motives of the trustee. This can take the form of abstract, generalized value congruence (Sitkin and Roth, 1993), which can be described as whether and to what extent the trustee has a motive to lie (Hovland et al., 1953). The purpose basis of trust reflects the attribution of these characteristics to the automation. Frequently, whether or not this attribution takes place will depend on whether the designer's intent has been communicated to the operator. If so, the operator will tend to trust the automation to achieve the goals it was designed to achieve. Often, the complexity, authority, and autonomy of the automation lead to a perceived animacy, in which the automation seems capable of independent and willful action independent of the operator (Sarter and Woods, 1994). In this situation, the intents that the operator infers may have little relationship to the purpose of the design, leading to a serious miscalibration of trust.

Although trust depends heavily on the interactions between an operator and the automation, the team and organizational structure within which they function may have an important effect on the diffusion of trust among co-workers. Communication with co-workers augments direct interaction with the automation and may have a strong influence on trust in the automation. A model of trust in automation and evolution of trust in multiperson groups that share responsibility for managing automation showed substantial influence of sharing automation-related information on trust and cooperation of other team members (Gao and Lee, 2006). In this situation, sharing information regarding the performance of the automation not only develops appropriate trust in the automation but also develops appropriate trust in team members who also manage the automation.

One of the ironies of automation is that operators often express a desire for simple and reliable automation, but want the automation to aid them with their most complex tasks (Tenney et al., 1998). Similarly, a highly sensitive warning system that results in many warnings can undermine trust because operators feel that the warnings fail to reflect the danger of the situation accurately (Gupta et al., 2002). These results suggest that understandable and reliable performance on easy tasks may not leave operators willing to rely on the automation to handle more difficult situations. Poor performance of automation on easy tasks severly undermines trust and reliance (Madhavan et al., 2006). Designing automation to promote appropriate trust may help resolve these conflicts. Ideally, trust in automation guides reliance when the complexity of a system makes complete understanding impractical and when the situation demands adaptive behavior (Lee and See, 2004). However, how to design automation to promote appropriate trust, particularly for complex automation that cannot be fully understood by the operator, is a substantial challenge.

One challenge to designing for appropriate trust is that trust has a strong emotional component and may respond to influences that would not be considered in the traditional information processing model that often underlies automation design. As an example, passenger attitudes towards an automated pilot depended on ticket price, suggesting price is used to infer quality. More importantly, inducing positive affect led to higher ratings, providing evidence that ratings of trust are strongly influenced by feelings (Hughes, et al., 2009). These results confirm a more general finding that emotion strongly influences attention, judgment and decision making with respect to automation interactions (Lee, 2006).

Job satisfaction and health often depend on automation in unexpected ways, in part because automation changes the relationship between operators and managers and between operators and work. The issues noted above have addressed primarily the direct performance problems associated with automation. The issue of job satisfaction goes well beyond performance to consider the morale and moral implications of a worker whose job is being changed by automation. Automation that is introduced merely because it increases the profit of the company may not necessarily be well received. Automation often has the effect of de-skilling a job, suddenly making obsolete skills that operators worked for years to perfect. Properly implemented, automation should re-skill workers and enable them to leverage their old skills into new ones that are extended by the automation. Many operators are highly skilled and proud of their craft; automation can thus either empower or demoralize them (Zuboff, 1988). Unhappy operators may fail to capitalize on the potential of an automated system or may even actively sabotage the automation, similar to what the Luddites did.

Automation can also change the relationship to work, increasing demands and decreasing decision latitude. Such an environment can undermine worker health, leading to problems ranging from increased heart disease to increased incidents of depression (Vicente, 1999). However, if automation extends the capability of the operator, it can enhance both satisfaction and health if operators are given sufficient decision latitude. As an example, night shift operators had greater decision latitude than that of day shift operators who worked under the eye of the managers. The night shift operators used this latitude to learn how to manage the automation more effectively (Zuboff, 1988). These effects demonstrate the need to consider the management and implementation of the automation.

2.4 Interaction between Automation Problems

Although described independently, the problems of automation often reflect an interacting and dynamic process. One problem may lead to another. Figure 2 summarizes the general problems with automation and identifies some of the important interactions. In many of these relationships, positive feedback reinforces the problem, creating vicious cycles that exacerbate the difficulty. As an example, inadequate training and skill loss may lead the operator to disengage from the monitoring task. This, in turn, will exacerbate the out-of-the-loop unfamiliarity, which will further undermine the operator’s skills, and so on. A similar dynamic exists between clumsy automation and automation-induced errors. Clumsy automation produces workload peaks, which increase the chance of mode and configuration errors. Recovering from these errors can further increase workload, and so on. Designing and implementing automation without regard for human capabilities and defining the human role as a by-product has been referred to as automation abuse (Parasuraman and Riley, 1997) and is likely to initiate the negative dynamics shown in Figure 2.

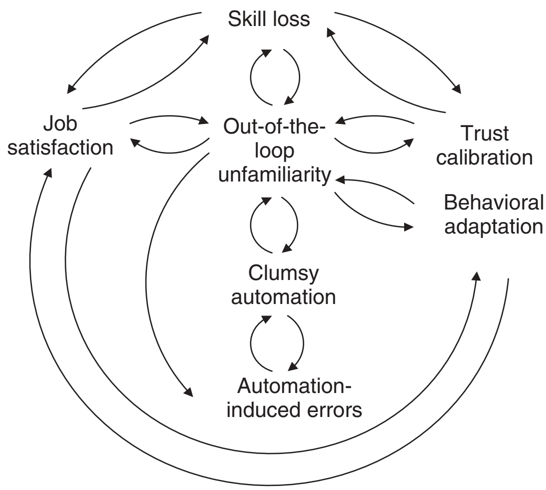


Figure 2 Interactions among the problems with automation.

3 TYPES OF AUTOMATION

The first step in minimizing the problems and maximizing the benefits of automation is to clarify what is meant by the term *automation*. Automation is not a homogeneous technology. Instead, there are many types of automation and each poses different design challenges. Automation can highlight, alert, filter, interpret, decide, and act for the operator. It can assume different degrees of control and can operate over time scales that range from milliseconds to months. The type of automation, its limits, the operating environment, and human characteristics interact to produce the problems just discussed. Descriptions of automation from different perspectives can reveal the implications of automation for system performance. One such description considers automation in terms of the four stages of human information processing and levels of automation (Parasuraman et al., 2000). Another description considers popular metaphors for automation: tools, prostheses, and agents. Finally, automation can be considered in terms of the scope of the tasks it supports: strategic, tactical, and operational. Any such low-dimensional description of a high-dimensional space will certainly fail to capture important distinctions; nevertheless, these perspectives can make meaningful distinctions that can support design decisions.

3.1 Information-Processing Stages and Levels of Automation

If automation is considered as technology that replaces the human in performing a function, it is then reasonable to describe automation in terms of the information-processing functions of the person. Although imperfect, the information process model of human cognition provides a useful engineering approximation that has been widely applied to system design (Broadbent, 1958; Rasmussen, 1986). The basic information-processing functions—information acquisition, information analysis, action selection, and action implementation—provide simple distinctions that can describe human and automation functions in a common language. A different type of automation corresponds to each stage of information processing. For each of these four functions, different degrees of automation are possible, ranging from full automation to manual control (Sheridan and Verplank, 1978). Information-processing stages and the degree of automation combine to describe a wide array of automation in a way that can guide automation design (Parasuraman et al., 2000).

Information acquisition automation refers to technology that complements the process of human attention. Such automation highlights targets (Yeh and Wickens, 2001; Dzindolet et al., 2002), provides alerts and warnings (Bliss, 1997; Bliss and Acton, 2003), and organizes, prioritizes, and filters information. Highlighting targets exemplifies a low degree of information acquisition automation because it preserves the underlying data and allows operators to guide their attention to the information they believe to be most critical. Filtering exemplifies a high degree of automation, and operators are forced to attend to the information the automation deems relevant. *Information analysis* refers to technology that supplants perception and working memory in the interpretation of a situation. Such automation supports situation assessment and diagnosis. As an example, critiquing a diagnosis generated by the operator represents a low degree of automation, whereas automation that provides a single diagnosis represents a high degree of automation. *Action selection automation* refers to technology that combines information in order to make decisions for the operator. Unlike information acquisition and analysis, action selection automation suggests or decides on actions using assumptions about the state of the world and the costs and values of the possible options (Parasuraman et al., 2000). Providing the operator with a list of suggested options represents a relatively low level of action selection automation. In contrast, automation that commands the operator to respond, as in the verbal "pull up, pull up" command of the ground proximity warning system, represents a high level of action selection automation. *Action implementation automation* supplants the operators' activity in executing a response. Olson and Sarter (2001) describe two degrees of action implementation automation *management by consent*, in which the automation acts only with the consent of the operator, and a greater degree of automation *management by exception*, in which automation initiates activities autonomously.

Each of these four stages of automation combines with the degree of automation to describe how the technology supplants the operator's role in perceiving and responding to the environment. Figure 3 shows two hypothetical systems. System B replaces the operator to a relatively high degree for all information-processing stages. In contrast, system A represents a generally lower level of automation, with only a moderate degree of automation in the information acquisition stage (Parasuraman et al., 2000).

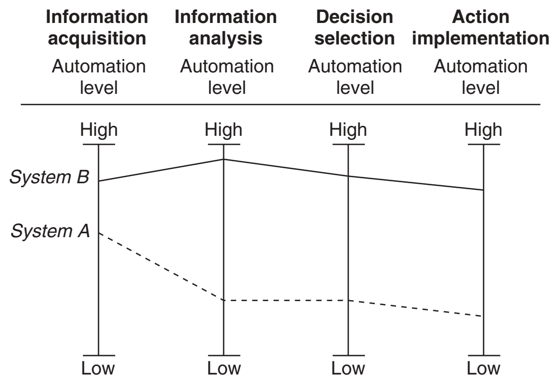


Figure 3 Two examples of automation defined by a profile of the degree of automation over the four information-processing stages. (From Parasuraman et al., 2000. Copyright © IEEE 2000.)

3.2 Tool, Prostheses, and Agents

As automation becomes more complex, considering it simply as a replacement for the information-processing functions of the operator may not differentiate adequately between important types of automation. In many situations, automation is not merely a system that operators engage and disengage. Often, automation consists of a complex array of modes and levels that operators must manage. Interacting with the automation involves coordinating multiple goals and strategies to select a mode of operation that fits the situation (Olson and Sarter, 2000). The simple distinction of engaging manual and automatic control does not capture the complexity of many types of automation. Important design issues emerge as automation evolves from a tool the operator uses to act on the environment to a prosthesis that replaces a human ability to an agent that acts on behalf of the operator. Increasing capacity of automation makes the metaphor of automation as a team member increasingly apt (Klein et al., 2004). The metaphors of automation as a tool, prosthesis, and agent provide complementary perspectives to the information-processing metaphor of automation.

Automation, considered as a *cognitive tool,* extends and complements human capabilities. According to the tool metaphor of automation, operators work directly on the environment, but automation augments their interactions. Just as a hammer augments human action in physical tasks, automation can augment operators in cognitive tasks (Woods, 1987). The benefit of automation as a tool is that its influence is clear and its failures are obvious. An example of automation as a tool that augments human capabilities is a haptic gas pedal, which increases the resistance as the driver approaches a car ahead. This contrasts with adaptive cruise control that automates car following or collision warnings that only alert the driver when he or she gets too close to the car in front. The continuous feedback of the haptic pedal provides the driver with a useful tool that improves car-following performance (Mulder et al., 2008)

Automation, considered as a *cognitive prosthesis,* acts to replace human function with a more capable computer version. Often, designers adopt this approach in an attempt to enhance system performance or safety by eliminating human error. A cognitive prosthesis eliminates a variable or error-prone aspect of human behavior and replaces it with a consistent computer-based process. The cost of this approach is lost flexibility and reduced ability to adapt to unforeseen situations (Roth et al., 1988). For these reasons, the cognitive prosthesis approach is most appropriate for routine, low-risk situations where decision consistency is more important than adapting to unusual situations. Automation that must accommodate unusual circumstances should adapt a cognitive tool perspective that complements rather than replaces human decision making.

Automation considered as an *agent* acts as a semiautonomous partner with the operator. According to the agent metaphor, the operator no longer acts directly on the environment but acts through an intermediary agent (Lewis, 1998) or intelligent associate (Jones and Jacobs, 2000). As an agent, automation initiates actions that are not in direct response to operators' commands. The authority, autonomy, and complexity of many advanced automated systems make them seem like intentional agents to operators, even if the designers had not intended to adopt this metaphor (Sarter and Woods, 1997). This autonomy and authority can lead to instances of poor coupling and coordination breakdowns because the agents fail to communicate their intentions (Sarter and Woods, 2000; Hoc, 2001). One of the greatest challenges with automated agents is that of mutual intelligibility. Instructing the agent to perform even simple tasks can be onerous, but agents that try to infer operators' intent and act autonomously can surprise operators, who might lack mental models of agent behavior. One approach to improve operator–agent cooperation is for the agents to learn and adapt to the characteristics of the operator through a process of remembering what they have been told to do in similar situations (Bocionek, 1995). After the agent completes a task, it can be equally challenging to make the results meaningful to the operator (Lewis, 1998). Because of these characteristics, agents are most useful for highly repetitive and simple activities, where the cost of failure is limited. In high-risk situations, constructing effective management strategies and providing feedback to clarify agent intent and communicate behavior become critical (Olson and Sarter, 2000; Sarter, 2000).

The differences between automation as a tool, prosthesis, and agent reflect a shift in the locus of control. With a tool, the operator firmly maintains control, but with an agent, the locus of control is more ambiguous and may pass back and forth between the operator and the automation. Ambiguity in the locus of control introduces important considerations regarding inferred intent and the dynamic coordination of actions (Woods, 1994).

The metaphors of tool, prosthesis, and agent complement the information-processing description of automation in important ways. The information-processing metaphor emphasizes the idea that automation replaces the person in performing a function but that function and system remain unchanged. Other metaphors, such as that of automation as an agent, emphasize the far-reaching changes that automation may induce. Rarely is automation a simple replacement of the human, rather, as Woods (1994, p. 4) describes, "technology change produces a complex set of effects. In other words, automation is a wrapped package—a package that consists of changes on many different dimensions bundled together as a hardware/software system." Just as the information-processing metaphor of automation leverages a long history of experimental psychology research, the agent metaphor may leverage recent developments in distributed cognition and team effectiveness (Seifert and Hutchins, 1992; Hutchins, 1995). Such a shift may lead to a change in the boundaries that define the unit of analysis, from one centered on a single operator and a single element of automation to one that considers multioperator, multiautomation interactions (Hollan et al., 2000; Gao and Lee, 2004).

3.3 Multilevel Control

The scope of automation varies dramatically, from decision support systems that guide corporate strategies over months and years to antilock brake systems that modulate brake pressure over milliseconds. Substantially different human limitations govern operator interaction with automation at these extremes. A three-level structure that has been used to describe driver behavior seems appropriate for discussing the more general issue of human–automation coordination (Michon, 1985; Ranney, 1994). Figure 4 shows three levels of control that provide a framework for considering issues of coordination and communication of intent. Each level of the figure defines a different level of control that could be supported by a different type of automation. *Strategic automation* concerns balancing values and costs as well as defining goals; *tactical automation*, on the other hand, involves priorities and coordination. Finally, *operational automation* has to do with perceptual cues and motor response.

The bottom of Figure 4 shows operational automation, which governs system behavior over the span of approximately 0.5–5 s. Automation at this level concerns the moment-to-moment control of dynamic processes. An example in the driving domain is ACC, which controls the speed of the car and its distance to the vehicle ahead. The middle of Figure 4 shows tactical automation, which governs system response over a time span of seconds to minutes. In driving, this automation would include route guidance systems that notify drivers of upcoming turns. At the top of the figure is strategic automation, which governs behavior from minutes to days. In driving, this automation helps drivers to select routes and plan trips.

The multilevel control perspective shown in Figure 4 identifies design considerations for the different types of automation and the interaction between different

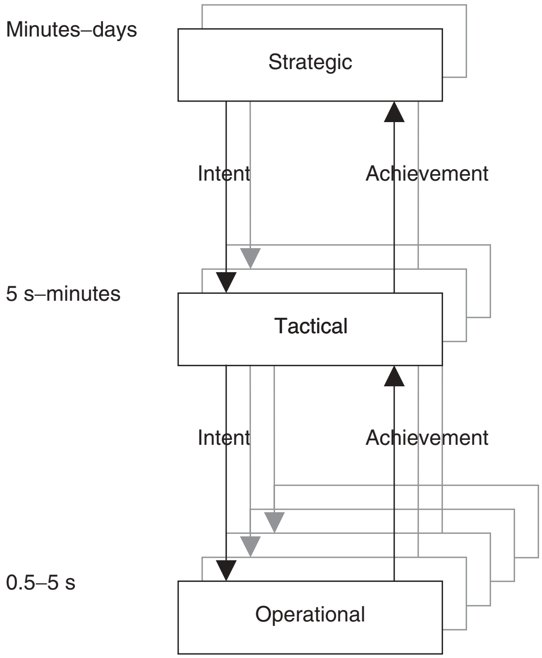


Figure 4 Strategic, tactical, and operational automation describe types of automation that reveal important coordination and feedback requirements.

elements of automation. First, automation at one level may have unanticipated effects on behavior at another level. For example, automatic control at the lower level might lead people to adopt different behaviors at a higher level, such as when ACC reduces the attention needed in routine car following at the operational level and influences decisions at the tactical level, such as deciding to engage in a cell phone conversation. Second, time constants have a critical effect on monitoring and control behavior. Detection of low-frequency events requires sustained monitoring best suited to time scales at the operational level (0.5–5 s), but such events often occur on a time scale that is orders of magnitude greater. At the other extreme are systems that demand responses on a time scale so short that it exceeds human capabilities. For these systems, automation may need to assume final authority for actions (Moray et al., 2000; Inagaki, 2003). The three-level structure highlights qualitative differences in the time constants of system control that automation design should consider (Hoc, 1993). Third, this perspective highlights the critical issue of communicating intent and the achievement of intent. Figure 4 highlights this requirement because automation at the operational level must be coordinated to achieve the intent developed at the tactical level. Adequate performance of an element of automation at the operational level does not guarantee success at the tactical level unless it is coordinated properly. Automation at one level of control must be managed to minimize interference between agents that might otherwise jeopardize achieving common tasks at another level of control (Hoc, 2001). Finally, Figure 4 points to the need to consider what some have termed *macrocognition* (Klein et al., 2003). Macrocognitive processes include situation assessment, planning, and coordination. Typical laboratory studies of automation have focused on *microcognition*, associated with operational and tactical levels; however, many critical problems with automation lie at the strategic level and in the interaction between the strategic and tactical levels.

The term *automation* represents a broad array of technology, and no one dimension or framework will capture the many factors that contribute to the problems often encountered with its implementation. Metaphors of information-processing systems, tools, prostheses, agents, and multilevel control all provide complementary perspectives on the nature of automation and how it influences operator performance. These perspectives are not mutually exclusive. A given instance of automation could be described using any or all of the three perspectives. Each provides a different description to guide automation design. Similarly, each perspective provides a partial and distorted description of the true complexities of automation. Although each perspective is limited, each can enhance our understanding of human–automation interaction.

4 STRATEGIES TO ENHANCE HUMAN–AUTOMATION INTERACTION

Defining the problems encountered with automation should instill caution in those who believe that automation can enhance system performance and safety by replacing the human operator. The perspectives on the nature and types of automation reveal the complexity of automation. Neither caution nor perspective, however, is sufficient to develop successful automation. In this section we describe specific strategies for designing effective automation, which include:

- Fitts's list and function allocation
- Dynamic function allocation (adaptable and adaptive automation)
- Matching automation to human performance characteristics
- Representation aiding and multimodal feedback
- Matching automation to mental models
- Formal automation analysis techniques

4.1 Fitts's List and Function Allocation

One approach to automation is to assess each function and determine whether a human or automation would perform that function better (Kantowitz and Sorkin, 1987; Sharit, 2003). Functions better performed by automation are automated and the operator remains responsible for the rest and for recovering during the periodic failures of the automation. Fitts's list provides a heuristic basis for determining the relative performance of humans and automation for each function (Fitts,

Table 1 Fitts's List: Relative Strengths of Automation and Humans for the Four Information-Processing Stages

Information-Processing Stage	Humans Are Better At:	Automation Is Better At:
Information acquisition	Detecting small amounts of visual, auditory, or chemical signals	Monitoring processes
	Detecting a wide range of stimuli	Detecting signals beyond human capability
Information analysis	Perceiving patterns and making generalizations	Ignoring extraneous factors and making quantitative assessments
	Exercising judgment	Consistently applying precise criteria
	Recalling related information and developing innovative associations between items	Storing information for long periods and recalling specific parts and exact reproduction
Action selection	Improvising and using flexible procedures	Repeating the same procedure in precisely the same manner many times
	Reasoning inductively and correcting errors	Reasoning deductively
Action implementation	Switching between actions as demanded by the situation	Performing many complex operations at once
	Adjusting dynamically to a wide range of conditions	Responding quickly and precisely

1951). Table 1 shows a revised Fitts list for the stages of automation identified earlier. The relative capability of the automation and human depend on the stage of automation (Sheridan, 2000).

Using the heuristics in Table 1 to determine which functions should be automated mitigates skill loss and lack of training by clearly identifying the human role in a system. This approach also enhances job satisfaction by designing a role for the operator that is compatible with human capabilities. Ideally, the function allocation process should not focus on what functions should be allocated to the automation or to the human but should identify how the human and the automation can complement each other in jointly satisfying the functions required for system success (Hollnagel and Bye, 2000).

Applying the information in Table 1 to determine an appropriate allocation of function has, however, substantial weaknesses. One weakness is that there are many interconnections between functions. Any description of functions is a somewhat arbitrary decomposition of activities that masks complex interdependencies. As a consequence, automating functions as if they were independent has the tendency to fractionate the operator's role, leaving the operator with only those tasks too difficult to automate (Bainbridge, 1983). Automation must be designed to support the job of the operator as an integrated whole. Another weakness with this approach is the situation dependence of the automation and human performance. The same function may require improvisation in some circumstances and precise application of a fixed response in others. Another weakness is that the work and the automation coevolve, with the automation making unanticipated work practices possible and the work leading to unanticipated applications of the automation (Dearden et al., 2000). A final weakness with function allocation using Fitts's list is the diminishing list of situations in which human abilities exceed those of the automation. Strict adherence to the application of Fitts's list to allocate functions between people and machines has been widely recognized as problematic (Parasuraman et al., 2000; Sheridan, 2000).

Although imperfect, Table 1 contains some general considerations that can improve design. People tend to be effective with complete patterns and less so with highly precise repetition. Human memory tends to organize large amounts of related information in a network of associations that can support effective judgments requiring the consideration of many factors. People also adapt, improvise, and accommodate unexpected variability. For these reasons it is important to leave the "big picture" to the human and the details to the automation (Sheridan, 2002).

4.2 Dynamic Function Allocation: Adaptable and Adaptive Automation

Using Fitts's list or some other method to allocate functions between humans and automation results in static function allocation in which the division of labor is fixed by the designer. Functions once performed by the human are now performed by automation. Static allocation of function contrasts with dynamic allocation of function, in which adaptable and adaptive automation makes it possible to adjust the division of labor between the human and the automation over time (Scerbo, 1996; Sarter and Woods, 1997). Dynamic allocation of function addresses the need to adjust the degree and type of automation according to individual differences, the state of the operator, and the state of the system. Adaptable and adaptive automation is often preferable to automation that is fixed and rigid.

Adaptable automation is that which the operator can engage or disengage as needed. The operator adapts the level and type of automation to the situation. Giving operators the option of manual or automatic control can be more effective than making available only automatic or only manual control (Harris et al., 1995).

More generally, adaptable automation gives operators additional degrees of freedom needed to accommodate unanticipated events (Hoc, 2000). The decision to rely on the automation or to intervene with manual control depends on many factors, including perceived risk, workload, trust, and self-confidence (Riley, 1989, 1994; Lee and Moray, 1994). To the extent that operators trust the automation appropriately and have appropriate self-confidence, they tend to rely on the automation appropriately and avoid some of the out-of-the-loop unfamiliarity problems. Allowing operators to transition easily between automatic and manual control can also mitigate clumsy automation. On the other hand, one of the critical deficiencies of adaptable automation is that it gives the operator the additional tasks of engaging and disengaging the automation. If the effort associated with these tasks is great, adaptable automation can increase the workload of demanding situations and thus become an example of clumsy automation.

Adaptive automation goes a step further than adaptable automation by automatically adjusting the level of automation based on the operator's performance, the operator's state, or the task situation (Rouse, 1988; Byrne and Parasuraman, 1996). Often, adaptive automation focuses on increasing the level of automation when either the operator's workload increases or the operator's capacity decreases. One way to estimate operator workload is through physiological measures such as heart rate and electroencephalography (EEG) signals (Byrne and Parasuraman, 1996). For example, it is possible to moderate an operator's workload by using closed-loop control algorithms to adjust the level of automation according to the operator's EEG signal (Prinzel et al., 2000). Other estimates of workload depend on models that relate the task situation to expected cognitive load and operator performance. For example, by combining operator performance and task variables it is possible to engage automation and mitigate predictable workload increases (Scallen and Hancock, 2001). Most promising is an approach that combines data from all three sources along with model-based predictions of workload. By engaging higher levels of automation during periods of high workload, adaptive automation promises to solve some of the problems of clumsy automation.

Alleviating overload is often the motive behind the development of adaptive automation. It may be equally important, however, to consider how it can mitigate problems of underload. Both underload and overload stress an operator's ability to respond (Hancock and Warm, 1989), and automation that returns tasks to the operator during underload situations may place operators in a less stressful situation. Similarly, operators who monitor reliable automation for long periods become surprisingly inefficient at detecting automation failures. Adaptive automation can mitigate this automation-induced complacency by returning manual control periodically to the operator (Parasuraman et al., 1996). Adaptive automation that used EEG signals led to higher levels of situation awareness and lower levels of workload compared to adaptable automation that required people to manage the users to engage the automation (Bailey et al., 2006).

Adaptive automation is a sort of meta-automation that can suffer from some of the same problems of automation if implemented improperly. Adaptive automation relieves the operator of the task of engaging and disengaging the automation, but it imposes the additional task of monitoring the adaptive automation, which can also increase workload (Kaber et al., 2001). In addition, adaptive automation faces challenging measurement and control problems. Adaptive automation depends on a precise measure of operator state, which can include physiological variables. If the time constant of these variables is longer than the time constant of the demands of the environment, automation will not adapt quickly enough. Even if operator state can be measured in a precise and timely manner, developing control algorithms that relate the operator state to an appropriate level of automation is difficult. Many of the limits of applying the Fitts list to static allocation of function also make dynamic allocation of function a challenge. Finally, even if an appropriate algorithm for adjusting the automation dynamically can be defined, the operator might respond in unexpected ways. For example, operators may manipulate their physiological state to influence the automation (Byrne and Parasuraman, 1996). Most important, operators may not understand the adaptive automation and so will view the system as behaving erratically. Such dynamic changes also introduce interface inconsistencies and increase the potential for mode errors.

4.3 Matching Automation to Human Performance Characteristics

Another approach to automation design considers how operators respond to different types of imperfect automation (Parasuraman et al., 2000). How well an operator is able to recognize and recover from automation failures often governs overall system performance. As a consequence, an important approach to automation design is to consider how human performance characteristics interact with the type of automation. The objective of this design approach is to minimize the tension that arises from mismatches between human performance characteristics and the type of automation (Sharit, 2003). A specific example of this approach considers the levels of automation and types of automation as defined by the stages of information processing. Primary considerations for automation design include workload, situation awareness, complacency, and skill maintenance (Parasuraman et al., 2000). These considerations do not specify a universally applicable degree of automation for each information-processing stage. Instead, appropriate automation design depends on the reliability of the automation and the consequences of failure as well as on technical and economic considerations (Parasuraman et al., 2000). In the context of air traffic control, human performance characteristics argue for the following upper bounds on the level of automation: information acquisition (high), information interpretation (high), action selection (medium), and action implementation (medium).

As an example, displays that indicate the status of the system (information interpretation automation) are preferable to those that advise the operator on how to respond (action selection automation) (Crocoll and Coury, 1990). Specifically, alerts regarding hazardous road conditions presented as a command (e.g., merge left) led to more dangerous lane changes compared to the same information presented as a notification (e.g., road construction in right lane) (Lee et al., 1999). Similar findings for a decision aid to help pilots make decisions regarding the dangers of aircraft icing suggest that status displays are preferable to command displays in high-risk domains where the automation is imperfect (e.g., space flight, medicine, and process control) (Sarter and Schroeder, 2001). Action implementation automation can be helpful when reliable but dangerously compelling when unreliable. Operators benefit more from action implementation automation than from action selection automation, but only when the automation performs reliably (Endsley and Kaber, 1999). Although a greater degree of automation enhances performance and reduces workload during routine situation, it can also reduce situation awareness and undermine the ability to respond—when the automation fails, operators perform better with lower levels of automation (Kaber et al., 2000). In addition to the reliability of the automation, time pressure influences the benefit of a greater degree of automation. Pilots preferred management by consent, a relatively low level of automation; however, during periods of high time pressure and high workload, they preferred management by exception, a higher level of automation (Olson and Sarter, 2000).

Expert systems represent a high degree of decision automation that has frequently failed to meet expectations. Typically, an expert system acts as a prosthesis, supposedly replacing flawed and inconsistent human reasoning with more precise computer algorithms. Unfortunately, the level of automation associated with such an approach often conflicts with the range of situations the automation must face: The system gives the wrong answer when confronted with cases for which the automation is not fully competent. In addition, the operator typically plays a passive role such as entering data or assessing automation decisions, which leads to brittle failures (Roth et al., 1988).

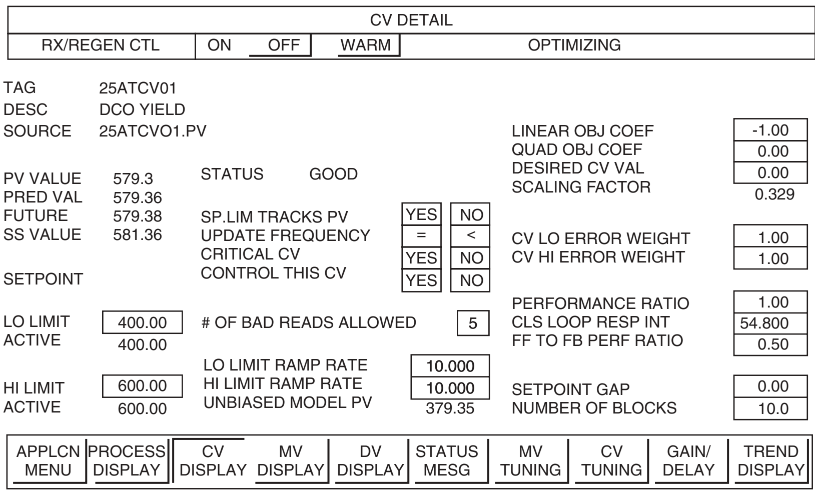
A lower degree of automation, which places the automation in the role of critiquing the operator, has met with much more success. In critiquing, the computer presents alternative interpretations, hypotheses, or choices that complement those of the operator (Guerlain et al., 1999; Sniezek et al., 2002). A specific example is a decision support system for blood typing (Guerlain et al., 1999). Rather than using the expert system as a cognitive prosthesis to identify blood types, the critiquing approach suggests alternative hypotheses regarding possible interpretations of the data. In cases where the automation was fully competent, the operators made correct diagnoses 100% of the time, compared to 33–63% for those without the critiquing system. In cases where the critiquing system was not fully competent, performance degraded gracefully and operators still correctly diagnosed 32% more cases than those without the critiquing system. In situations where the automation is imperfect or the cost of failure is high, a lower level of automation, such as that used in the critiquing approach, is less likely to induce errors. Although much of the benefit of a critiquing system stems from the lower degree of automation and the greater involvement of the operator in the decision process, representation aiding plays an important role in supporting efficient operator–automation interaction.

4.4 Representation Aiding and Multimodal Feedback

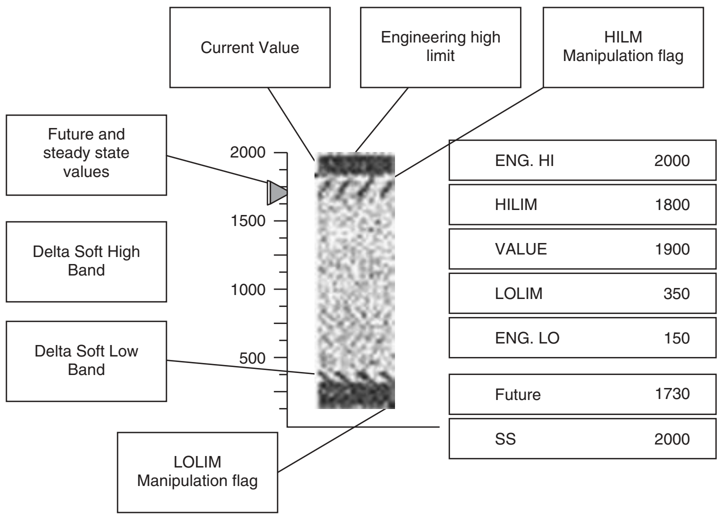
Even if the type of automation is well matched to the task situation and human capabilities, inadequate feedback can undermine human–automation interaction. Inadequate feedback underlies many of the problems with automation from developing appropriate trust and clumsy automation to the out-of-the-loop phenomenon (Norman, 1990). However, providing sufficient feedback without overwhelming the operator is a critical design challenge. Poorly presented or excessive feedback can increase operator workload and undermine the benefits of the automation (Entin et al., 1996). In addition, without the proper context, abstraction, and integration, information regarding the behavior of complex automation may not be understandable. Representation aiding and multimodal feedback are two approaches that can help people understand how the automation works and how it is performing.

Representation aiding capitalizes on the power of visual perception to convey complex dynamic relationships. For example, graphical representations for pilots can augment the traditional airspeed indicator with target airspeeds and acceleration indicators. Integrating this information into a traditional flight instrument allows pilots to assimilate automation-related information with little extra effort (Hollan et al., 2000). Using a display that combines pitch, roll, altitude, airspeed, and heading can directly specify task-relevant information such as what is “too low” (Flach, 1999). Integrating automation-related information with traditional displays and combining low-level data into meaningful information are two important ways to enhance feedback without overwhelming the operator.

In regard to process control, Guerlain et al. (2002) identified three specific strategies for visual representation of complex process control algorithms. First, create visual forms whose emergent features correspond to higher order relationships. Emergent features are salient symmetries or patterns that depend on the interaction of the individual data elements. A simple emergent feature is *parallelism*, which can occur with a pair of lines. Higher order relationships are combinations of the individual data elements that govern system behavior. The boiling point of water is a higher order relationship that depends on temperature and pressure. Second, use appropriate visual features to represent the dimensional properties of the data. For example, magnitude is a dimensional property that should be displayed using position or size on a visual display, not color or texture. Third, place data in a meaningful context. The meaningful context for any variable depends on what



(*a*)



(*b*)

Figure 5 (*a*) Comparison of a traditional interface for automation; (*b*) example of representation to support operator understanding of automation.

comparisons need to be made. For automation, this includes the allowable ranges relative to the current control variable setting and the output relative to the desired level. Figure 5 shows some of the principles of representation aiding—use analog rather than digital or text, provide meaningfully integrated rather than raw data, and provide a context to support visual rather than mental comparisons.

Representation aiding makes it more likely that operators will trust automation more appropriately. However, trust also depends on more subtle elements of the interface (Lee and See, 2004). In many cases, trust and credibility depend on surface features of the interface that have no obvious link to the true capabilities of the system (Briggs et al., 1998; Tseng and Fogg, 1999). For example, in an online survey of over 1400 people, Fogg et al. (2001b) found that for websites credibility depends heavily on "real-world feel," which is defined by factors such as response speed, a physical address, and photos of the organization. Similarly, a formal photograph of the author enhanced trustworthiness of a research article, whereas an informal photograph decreased trust (Fogg et al., 2001a). These results show that trust tends to increase when information is displayed in a way that provides concrete details that are consistent and clearly organized.

A similar pattern of results appears in studies of automation for target detection. Increasing image realism increased trust and led to greater reliance of the cueing information (Yeh and Wickens, 2001). Similarly, the tendency of pilots to follow the advice of the system blindly increased when the aid included detailed pictures (Ockerman, 1999). Just as highly realistic images can increase trust, degraded imagery can decrease trust, as was shown in a target cueing situation (MacMillan et al., 1994). Adjusting image quality and adding information to the interface regarding the capability of the automation can promote appropriate trust. In a signal detection task, the reliability of the sources was coded with different levels of luminance, leading participants to weigh reliable sources more than unreliable ones (Montgomery and Sorkin, 1996). These results suggest that the particular interface form can increase the level of trust, particularly the emphasis on concrete realistic representations.

Trust and reliance can also be enhanced with information that conveys the performance and expected value of automation. Such information can address appraisal errors—failures to properly judge the benefit of the automation. In one study, performance feedback reduced disuse rates from 84 to 55% (Beck et al., 2007). This result suggests that even when operators understand the expected value of the automation, they persist in disuse, indicating a John Henry effect in the form of intent errors. Intent errors were mitigated with scenario training that conveyed the appropriate thought process for interpreting automation suggestions. When combined with feedback, scenario training reduced disuse to 29% (Beck et al., 2007). The degree of personal investment operators have in performing the task has a strong influence on the prevalence of intent errors and, consequently, the importance of scenario training (Beck et al. 2009). Such

Representation aiding tends to focus on interfaces that require focal as opposed to peripheral vision. Operators already face substantial demands on focal vision, and presenting automation-related information in that channel may overwhelm the operator. *Multimodal feedback* provides operators with information through haptic, tactile, auditory, and peripheral vision to avoid overwhelming the operator. Haptic feedback has proved more effective in alerting pilots to mode changes in cockpit automation compared to visual cues (Sklar and Sarter, 1999). Pilots receiving visual alerts detected 83% of the mode changes; those with haptic warnings detected 100% of the mode changes. Importantly, the haptic warnings did not interfere with the performance of concurrent visual tasks. Similarly, peripheral visual cues also helped pilots detect uncommanded mode transitions and did not interfere with concurrent visual tasks any more than did currently available automation feedback (Nikolic and Sarter, 2001). Haptic warnings may also be less annoying and acceptable compared to auditory warnings (Lee et al., 2004). Although promising, multimodal interfaces lack the resolution of visual interfaces, making it difficult to convey complex relationships and detailed information.

4.5 Matching Automation to Mental Models

The complexity of automation sometimes makes it difficult to convey its behavior using representation aiding or multiple-modal feedback. Sometimes a more effective strategy is to simplify the automation (Riley, 2001) or to match its algorithms to the operators' mental model (Goodrich and Boer, 2003). This is particularly true when a technology-centered approach to automation design has created an overly complex array of modes and features. The out-of-the-loop unfamiliarity problems result partially from the difficulties that operators have in generating correct expectations for the counterintuitive behavior of complex automation. Automation designed to perform in a manner consistent with operators' preferences and expectations can make it easier for operators to recognize failures and intervene.

Adaptive cruise control is a specific example of where matching the mental model of the operator may be quite effective. Because drivers must focus their attention on the roadway, representation aiding could be distracting. Because ACC can apply only moderate levels of braking, drivers must intervene if the car ahead brakes heavily. If drivers must intervene, they must quickly enter the control loop because fractions of a second matter. If the automation behaves in a manner consistent with that of the driver, he or she will be more likely to detect and respond to the operational limits of the automation (Goodrich and Boer, 2003). To design an ACC algorithm consistent with drivers' mental models, driver behavior was partitioned according to perceptually relevant variables of inverse time to collision and time headway. Inverse time to collision (T_c^{-1}) is the relative velocity divided by the distance between the vehicles. Time headway (T_h) is the distance between vehicles divided by the velocity of the driver's vehicle. These variables define the boundary that separates speed regulation and headway maintenance from active braking associated with collision avoidance. Figure 6 shows this boundary in the space defined by time headway and inverse time

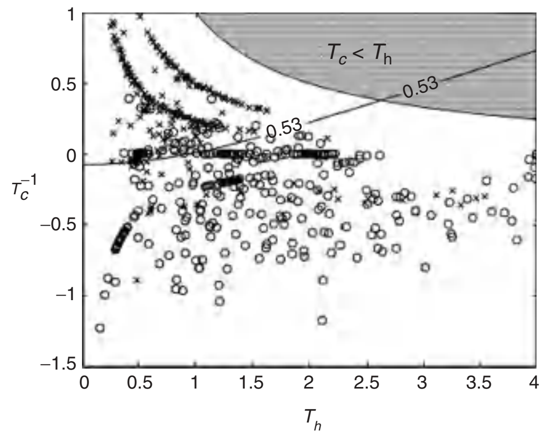


Figure 6 Driver braking behavior, showing a clear boundary between headway maintenance (◯) and collision avoidance (×) that could be used to define operational limits of ACC. (From Goodrich and Boer, 2003. Copyright © IEEE 2002.)

to collision. This boundary provides a template for designing ACC—the ACC should signal the driver to intervene as the driving situation crosses the boundary.

For situations in which the metaphor for automation is an agent, the mental model that people may adopt to understand the automation is that of a human collaborator. If the template for understandable automation is the operator's mental model, an agent should respond as would a human. Specifically, Miller (2002) suggests that computer etiquette may have an important influence on human–automation interaction. Etiquette may influence trust because category membership associated with adherence to a particular etiquette helps people to infer how the automation will perform. Specific rules for automation etiquette adapted from Miller and Funk (2001) include:

- Make many correct interactions for every erroneous interaction.
- Make it very easy to override the automation.
- Do not make the same mistake twice—stop a behavior if corrected by the operator.
- Do not enable interaction features just because they are possible.
- Explain what is being done and why.
- Be able to take instruction.
- Do not assume every operator is the same—be sensitive and adapt to individual, contextual, and cultural differences.
- Be aware of what the operator knows and do not repeat unnecessarily.
- Use multiple modalities to communicate.
- Try not to interrupt.
- Be cute only if it furthers specific interaction goals.

Developing automation etiquette could promote appropriate trust, but it could lead to inappropriate trust if people infer inappropriate category memberships and develop distorted expectations regarding the capability of the automation. Even in simple interactions with technology, people often respond as they would to another person (Reeves and Nass, 1996; Nass and Lee, 2001). If anticipated, this tendency could help operators develop appropriate expectations regarding the behavior of the automation; however, unanticipated anthropomorphism could lead to surprising misunderstandings of the automation.

An important prerequisite for designing automation according to the mental model of the operator is the existence of a consistent mental model. Individual differences may be difficult to accommodate. This is particularly true for automation that acts as an agent, in which a mental model–based design must conform to complex social and cultural expectations. In addition, the mental model must be consistent with the physical constraints of the system if the automation is to work properly (Vicente, 1990). Mental models often contain misconceptions, and transferring these to the automation could be counterproductive or deadly. Even if operators have a single mental model that is consistent with the system constraints, automation based on a mental model may not achieve the same benefits as automation based on more sophisticated algorithms. In this case, designers must consider the trade-off between the benefits of a complex control algorithm and the costs of a poorly understood system. Representation aiding can mitigate this trade-off.

4.6 Formal Automation Analysis Techniques

Effective representation aiding depends on identifying the relevant information needed to understand the behavior of the automation. With complex automation, this can be a substantial challenge. One approach to meeting this challenge is to use formal verification techniques (Leveson, 1995; Degani and Heymann, 2002). Specifically, state machines can define the behavior of the automation and the operator's model. The state machine that defines the operator's model is constructed from the training materials and the information available on the interface. State machines provide a formal modeling language to define mismatches between the operator's model of the automation and the automation. These mismatches cause automation-related errors and surprises to occur.

State machines identify the legal and illegal states defined by the task constraints that the automation and operator must satisfy. When the automation model enters an illegal state and the operator's model does not, the analysis predicts that the associated ambiguity will surprise operators and lead to errors (Degani and Heymann, 2002). Such ambiguities have been discovered in actual aircraft autopilot systems (Degani and Heymann, 2002). Mismatches between the operator and automation models indicate deficiencies in the operator's mental model that should be addressed by changing the automation, training, or interface (Heymann and Degani, 2007). The state machine formalism makes it possible to generate training and interface requirements automatically.

Often, designers overestimate the benefit of automation because of the surprising interactions between the automation, environment, and operator. Formal analysis that considers these interactions in terms of expected-value calculations can reduce the surprise and guide design. In the example of a rear-end collision warning system for cars, a Bayesian approach combined with signal detection theory shows that the posterior probability of a collision situation given a warning is surprisingly low because the base rate of collision situation is so low (Parasuraman et al., 1997). This analysis shows that the selection of a detection threshold should consider the base rate; otherwise, the relatively high rate of false alarms could undermine driver acceptance.

More generally, calculating the expected value of manual and automatic control provides a rigorous means of selecting the best alternative (Sheridan and Parasuraman, 2000). In the simplest case this involves comparing the expected value of the operator and automation response to a binary failure state—a system is either operating normally or it has failed. The expected-value calculation combines the benefits and costs of four general responses to the system: a true positive, a true negative, a false negative, and a false positive. The expected value of the automation and the expected value of the operator response depend on the costs of being wrong and the benefits of being correct, together with the prior probabilities of the failure and the probabilities of the automation and operator being wrong and correct. If the expected value for automatic control is greater than the expected value for manual control, automation should be implemented. A similar analysis shows that the time-dependent value of automation makes it reasonable to give the automation final authority in some situations, such as in guiding the pilot to make go/no go decisions in aborting a takeoff (Inagaki, 2003). A similar analysis might help designers balance the information-processing demands of feedback regarding automation behavior with the time demands of the situation. Experiments assessing human interaction with automation should consider this calculation in defining experimental conditions, defining the reward structure, and interpreting the participants' behavior (Bettman and Payne, 1990; Payne et al., 1992; Meyer, 2004); otherwise, it is impossible to differentiate automation bias from eutactic behavior.

An expected-value analysis provides a way to formalize the cost–benefit analysis that might otherwise be guided by the qualitative Fitts list heuristics. Although it promises to precisely quantify otherwise ambiguous decisions, estimating the numbers required to support the calculations can be a challenge. The costs and probabilities of rare, catastrophic events are notoriously difficult to estimate. More subtly, operator performance may affect the prior probabilities of events such that good operators experience fewer failures than do poor operators. In this situation, the automation will perform more poorly for better operators (Meyer and Bitan, 2002). Although precise probabilities and values may be difficult or impossible to estimate, such an approach is quite useful even if only relative benefits and costs of the automation and operator can be estimated (Sheridan and Parasuraman, 2000).

Simulation can also guide designers to consider the costs and benefits of automation more thoroughly. A simulation of a supervisory control situation shows that well-adapted operators are sensitive to the costs of engaging and disengaging automation (Kirlik, 1993). This simulation analysis identifies how the time costs of engaging the automation interact with the dynamics of the environment to undermine the value of the automation. A similar analysis argues that designers must make the normative strategy less effortful than competing strategies if operators are to use automation effectively (Todd and Benbasat, 2000). More generally, simulation models that capture the human performance consequences of different levels of automation reliability, and the environmental constraints are needed to support design. For example, a connectionist model of complacency provides a strong theoretical basis that accounts for empirical findings (Farrell and Lewandowsky, 2000). Cognitive architectures such as ACT-R also offer a promising approach to modeling human–automation interaction (Anderson and Libiere, 1998). Although ACT-R may not be able to capture the full complexity of this interaction, it may provide a useful tool for approximating the costs and benefits of various automation alternatives (Byrne and Kirlik, 2005).

5 EMERGING CHALLENGES

Substantial progress has been made regarding how to design automation to support people effectively. However, continuous advances in software and hardware development combined with an ever-expanding range of applications make future problems with automation likely. The following section highlights some of these emerging challenges. The first is the demands of managing a new type of automation, *swarm automation*, in which many semiautonomous agents work together. The second is the implication of automation in large interconnected networks of people and other automated elements, where issues of coordination and competition become critical. Automation in this environment requires considerations beyond those of the typical single operator interacting with one or two elements of automation. The third is the introduction of automation into daily life: specifically, automation in the car. These three examples represent some of the challenges associated with new types of automation, new types of human–automation organizations, and new application domains.

5.1 Swarm Automation

Swarm automation is an alternative approach to automation that may make it possible to respond to environmental variability while reducing the chance of system failure. These capabilities have important applications in a wide range of domains, including planetary exploration, unmanned aerial vehicle reconnaissance, landmine neutralization, or even data exploration, where hundreds of simple agents might be more effective than a single complex agent. Biology-inspired roboticists provide a specific example of swarm automation. Instead of the traditional approach of relying on one or two larger robots, they employ swarms of insect robots as an alternative (Brooks et al., 1990; Johnson and Bay, 1995). The swarm robot concept assumes that small machines with simple reactive behaviors can perform important functions more reliably and with lower power and mass requirements than can larger robots (Beni and Wang, 1993; Brooks and Flynn, 1993; Fukuda et al., 1998). Typically, the simple programs running on an insect robot are designed to elicit desirable emergent behaviors in the swarm (Sugihara and Suzuki, 1990; Min and Yin, 1998). For example, a large group of small robots might be programmed to search for concentrations of particular mineral deposits by building on the foraging algorithms of honeybees or ants.

In addition to physical examples of swarm automation, swarm automation has potential in searching large complex data sets for useful information. For example, the pervasive issue of data overload and the difficulties associated with effective information retrieval suggest a particularly useful application of swarm automation. Current approaches to searching large complex data sources, such as the Internet, are limited. People are likely to miss important documents, disregard data that represent a significant departure from initial assumptions, misinterpret data that conflict with an emerging understanding, and disregard more recent data that could revise interpretation (Patterson, 1999). These issues can be summarized as the need to broaden searches to enhance opportunity to discover highly relevant information, promote recognition of unexpected information to avoid premature fixation on a particular viewpoint or hypothesis, and manage data uncertainty to avoid misinterpretation of inaccurate or obsolete data (Woods et al., 1999). These represent important challenges that may require innovative design concepts and significant departures from current tools (Patterson, 1999). Just as swarm automation might help explore physical spaces, it might also help explore information spaces.

Managing swarm automation requires a qualitatively different approach than that of more traditional automation (Lee, 2001). Swarms of bees and ants, in which many simple individuals combine to behave as a single entity, provide some useful insights into the characteristics of swarm behavior and how they might be managed (Bonabeau et al., 1997). A defining characteristic of swarm behavior is that it emerges from parallel interaction between many agents. For example, swarms of bees adjust their foraging behavior to the environment dynamically in a way that does not depend on the performance of any individual. A colony of honeybees functions as a large, diffuse, amoeboid entity that can extend over great distances and simultaneously tap a vast array of food sources (Seeley, 1997). Direct control of this emergent behavior is not possible. Instead, mechanisms influencing individual elements of the swarm indirectly influence swarm behavior. Two particularly important mechanisms are positive feedback and random variation. Positive feedback reinforces existing activities, and random variation generates new activities and encourages adaptation (Resnick, 1991). One way that positive feedback and random variation combine to influence behavior is through *stimergy*, in which communication and control occur through a dynamically evolving structure. Through stimergy, social insects communicate directly through the products of their work (e.g., the bees' honeycomb and the termites' chambers). A specific example of stimergy is the pheromone trail that guides the self-organizing foraging behavior of ants. Stimergy in foraging behavior involves a trade-off of speed of trail establishment and search thoroughness; A trail that is more quickly established will sacrifice the thoroughness of the search. Stimergy represents a powerful alternative to a static set of instructions that specify a sequence of activity. Parallel interaction between many agents, positive feedback, random variation, and stimergy make it possible for many simple individuals to produce complex group behavior (Bonabeau et al., 1997). However, such control mechanisms may be difficult for operators to understand.

The concept of hortatory control describes some of the challenges of controlling swarm automation. Hortatory control applies in situations where the system being controlled retains a high degree of autonomy and operators must exert indirect rather than direct control (Murray and Liu, 1997). Interacting with swarm automation requires people to consider swarm dynamics independent of the individual agents. In these situations it is most useful for the operator to control parameters affecting group rather than individual agents and for the operators to receive feedback about group rather than individual behavior. Swarm automation has great potential to extend human capabilities, but only if a thorough empirical and analytic investigation identifies the display requirements, feasible control mechanisms, and range of swarm dynamics that can be comprehended and controlled by humans.

5.2 Management of Complex Networks of Operators and Automation

As automation becomes pervasive, it creates complex networks of increasingly tightly coupled elements. In this situation, the appropriate unit of analysis may shift from a single operator interacting with a single element of automation to that of multiple operators interacting with multiple elements of automation. Important dynamics can only be explained with this more complex unit of analysis. More so than single-operator situations, in these highly coupled systems, poor coordination between operators and inappropriate reliance on automation can degrade the decision-making performance and lead to catastrophes (Woods, 1994). As an example, the largest power grid failure in the nation's history occurred on August 14, 2003. In this failure, the flow of approximately 61,800 MW of electricity was disrupted, leaving 50 million customers from Ohio to New York and parts of Canada without power. An important contribution to this event was a lack of cooperation between two regional electrical grid operators that monitor the same region. These operators manage the flow of the electricity from suppliers to distributors. Poor communication and a failure to exchange detailed information on their operations prevented them from understanding and responding to changes in the power grid. Similar failures occur in supply chains as well as petrochemical processes, where people and automation sometimes fail to coordinate their activities.

Supply chains represent an increasingly important example of multioperator multiautomation. A supply chain is composed of a network of suppliers, transporters, and purchasers who work together, usually as a decentralized virtual company, to convert raw materials into products for end users. The growing popularity of supply chains reflects the general trend of companies to move away from vertical integration, where a single company converts raw materials into products for end users. Many manufacturers increasingly rely on supply chains; a typical U.S. company purchases 55% of the value of its products from other companies (Dyer and Singh, 1998). Efficient supply chains play a critical role in maintaining the economic health of the U.S. economy.

However, supply chains suffer from serious problems that erode their promised benefits. One is the *bullwhip effect*, in which small variations in end-item demand induce large-order oscillations, excess inventory, and backorders (Sterman, 1989). This effect can have enormous consequences on a company's efficiency and value. As an example, news reports of supply chain glitches associated with the bullwhip effect resulted in abnormal declines of 10.28% in companies' stock price (Hendricks and Singhal, 2003). Automation that forecasts demands can moderate these oscillations (Lee and Whang, 2000; Zhao and Xie, 2002). However, people must trust and rely on that automation, and substantial cooperation between supply chain members must exist to share such information.

Another major problem facing supply chains is the breakdown in cooperation as relationships between members of a supply chain devolve through an escalating series of conflicts that has been termed a *vicious cycle* (Akkermans and van Helden, 2002). Such conflicts can have dramatic negative consequences for a supply chain. For example, a strategic alliance between Office Max and Ryder International Logistics devolved into a legal fight in which Office Max sued Ryder for $21.4 million and then Ryder sued Office Max for $75 million (Handfield and Bechtel, 2002). Beyond the legal costs, these breakdowns can threaten competitiveness and undermine the market value of the company (Dyer and Singh, 1998). Vicious cycles also undermine information sharing, which can exacerbate the bullwhip effect. Even with the substantial benefits of cooperation, supply chains frequently fall into a vicious cycle in which poor cooperation leads to further poor cooperation. Trust between people plays a critical role in developing and sustaining cooperative relationships. People must trust each other to share information, and this trust can be undermined if poorly managed automation of one supply chain member compromises the success of another.

The bullwhip effect and vicious cycles and other supply chain problems reflect the influence of inappropriate actions at the local level that drive dysfunctional network dynamics. These effects are unique to highly coupled networks and require a unit of analysis that goes beyond the single person interacting with a single element of automation. As exemplified by the bullwhip effect and vicious cycles, the problems of supply chain management reflect generic challenges in using decentralized control to achieve a central objective. Decentralized networks promise efficiency and the capacity to adapt to unexpected perturbations, but their complexity and inefficient information sharing can lead people to respond to local rather than global considerations. Automation can alleviate the tendency for attention to local goals to magnify a small disturbance into a widespread disruption, or properly designed, it may alleviate this tendency. However, too little or too much trust in automation leads to inappropriate reliance, which can induce dysfunctional dynamics, such as the bullwhip effect and vicious cycles (Lee and Gao, 2006).

Other domains share the general promise and pitfalls of modern supply chain management. For example, power grid management involves a decentralized network that makes it possible to supply the United States efficiently with power, but it can fail catastrophically when cooperation and information sharing break down (Zhou et al., 2003). Similarly, datalink-enabled air traffic control makes it possible for pilots to negotiate flight paths efficiently, but it can fail when pilots have trouble anticipating the complex dynamics of the system (Olson and Sarter, 2001; Mulkerin, 2003). Also, grid computing makes its enormous computing power available for use by many independent agents, but it can fail if load balancing and job scheduling do not consider global considerations (Lorch and Kafura, 2002; Chervenak et al., 2003). Overall, technology is creating many highly interconnected networks that have great potential but that also raise important concerns. Resolving these concerns depends on designing effective multioperator, multiautomation interactions.

5.3 Driving and Roadway Safety

Much of the existing research on automation has focused on operators of large complex systems for which expensive automation has been practical to develop. As computer and sensor technology becomes more affordable, automation will become more common in systems encountered in day-to-day life. Automation for cars and trucks is an example of automation that will touch the day-to-day lives of many people. Vehicle automation may touch more peoples' lives and have a greater safety consequence than any other type of automation. In the United States alone, people drive over 2 trillion miles a year in cars and light trucks (Pickrell and Schimek, 1999). The safety consequence is equally impressive. Over 6 million crashes kill approximately 42,000 people each year and result in an economic cost of over $164 billion per year (Wang et al., 1999). Motor vehicle crashes are also the leading cause of workplace injuries, being responsible for 42% of work-related fatalities (Bureau of Labor Statistics, 2003). Automation in cars and trucks, like that of increasing automation in other parts of daily life, has the potential to influence the safety and comfort of many people.

Functions that vehicle automation might support range from routing and navigation to collision avoidance and vehicle control (Lee, 1997; Young and Stanton, 2007). Table 2 shows some of the many examples of current and potential types of vehicle automation. Currently, examples include navigation systems that use GPS data and electronic map databases that give drivers turn-by-turn directions. Also, adaptive cruise control uses sensors and new control algorithms to extend cruise control so that cars slow down automatically and maintain a safe distance from the car ahead. Many vehicles even have a system that uses sensor data (e.g., airbag deployment) to detect a crash, calls for emergency aid, and then transmits the crash location using the car's GPS. The potential of automation to enhance the safety and comfort of drivers is substantial.

Designing automation to support driving confronts many of the same challenges as those found with automation in other domains. Sensor imperfections and complexity of the driving environment make adaptive cruise control and collision warning systems fallible. Recent studies suggest that adaptive cruise control may induce complacency and the potential of overtrust. Specifically, many drivers intervene too slowly to prevent a collision when the adaptive cruise control fails to brake (Stanton et al., 1997). Behavioral adaptation also threatens to undermine the safety benefits of automation. Automation aimed to enhance safety, such as an ABS,

Table 2 Automation for Driving and Other In-Vehicle Technology

General Functions	Specific Examples
Routing and navigation	Trip planning, multimode travel coordination and planning, predrive route and destination selection, dynamic route selection, route guidance, route navigation, automated toll collection, route scheduling, posttrip summary
Motorist services	Broadcast services/attractions, services/attractions directory, destination coordination, delivery-related information
Augmented signage	Guidance sign information, notification sign information, regulatory sign information
Safety and warning	Immediate hazard warning, road condition information, aid request, vehicle condition monitoring, driver monitoring, sensory augmentation
Collision avoidance and vehicle control	Forward object collision avoidance, road departure collision avoidance, lane change and merge collision avoidance, intersection collision avoidance, railroad crossing collision avoidance, backing aid, vehicle control
Driver comfort, communication, and convenience	Real-time communication; asynchronous communication; contact search and history; entertainment and general information; heating, ventilation, air conditioning, and noise

Source: Adapted from Lee and Kantowitz (2005).

has not produced the expected safety benefits because drivers with an ABS tend to change their driving behavior and follow more closely (Sagberg et al., 1997). A similar response may occur with collision warning systems that aim to give drivers advance notice of impending collisions. Such systems may lead some drivers to think they can safely engage in distracting activities, such as reading or watching DVDs, while driving. Understanding how to develop vehicle automation to enhance safety such that behavioral adaptation does not erode its benefits is a critical challenge.

Another challenge that confronts the design of vehicle automation is the potential for driver confusion in the face of many poorly integrated systems. Similar problems of automation coordination and integration have occurred with maritime navigation aids (Lee and Sanquist, 2000), flight management systems (Sarter and Woods, 1995), and medical devices (Cook et al., 1990a). Already, early examples of vehicle automation show the substantial confusion and frustration associated with poorly integrated systems, such as the recent controversy and confusion regarding the 700 features of the BMW iDrive (Norman, 2003). Forward object, road departure, lane change, and intersection collision warning systems may all populate the car of the future, and identifying which warning has been activated may be a challenge for drivers. To avoid such confusion requires a design approach that considers the overall driving ecology and the information needed to negotiate it rather than an approach focused on sensor technology and arbitrarily defined collision types.

Unlike operators of automation in domains such as aviation and process control, drivers do not receive specific training on how to operate particular features of their car. In addition, drivers belong to a very heterogeneous group that spans a wide range of age, experience, and goals for driving. The difficulty of providing systematic training for automotive automation and the diversity of drivers make it likely that many drivers will misunderstand and misuse vehicle automation. Drivers misunderstand even a simple system, such as an ABS, and benefit from training on how to use it (Mollenhauer et al., 1997). More complex systems such as adaptive cruise control may confuse drivers, particularly as they move from a vehicle they are accustomed to driving to one they are not (e.g., a rental car). Ensuring that all drivers are properly trained is much more difficult than ensuring that process control operators or pilots understand the automation they manage. Automation that affects day-to-day life, such as vehicle automation, faces the particular challenges of being understood and used appropriately by a highly diverse array of potential users.

6 AUTOMATION — DOES IT NEED US?

The Luddites faced the prospect of automation changing their lives, and we face a similar prospect today. Increasingly sophisticated automation makes it possible to replace the human in many situations, and the situations in which humans outperform automation are diminishing rapidly. Although the need for human adaptability, creativity, and flexibility makes complete automation of most systems infeasible, the increasing capability of automation may eliminate even these reasons to include human operators. Soon, automating based on the criterion of whether the human or machine is better suited to perform a task may be irrelevant. This situation requires a deeper consideration of the purpose of technology (Hancock, 1996). Although automation allows people to avoid dangerous and unpleasant situations, unrestrained automation may eliminate activities that provide intrinsic enjoyment and purpose to life (Nickerson, 1999). Ironically, automating everything that is technologically possible or even everything that enhances system efficiency and safety may have the unanticipated effect of diminishing the lives of the people that automation should ultimately serve. Like the Luddites, we may ultimately need to confront the issue of whether automation needs us. “At least we have it in our power to say no to new technology, or do we?”(Sheridan, 2000, p. 203).

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