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# Humans and Automation: Use, Misuse, Disuse, Abuse

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This paper addresses theoretical, empirical, and analytical studies pertaining to human use, misuse, disuse, and abuse of automation technology. *Use* refers to the voluntary activation or disengagement of automation by human operators. Trust, mental workload, and risk can influence automation use, but interactions between factors and large individual differences make prediction of automation use difficult. *Misuse* refers to overreliance on automation, which can result in failures of monitoring or decision biases. Factors affecting the monitoring of automation include workload, automation reliability and consistency, and the saliency of automation state indicators. *Disuse,* or the neglect or underutilization of automation, is commonly caused by alarms that activate falsely. This often occurs because the base rate of the condition to be detected is not considered in setting the trade-off between false alarms and omissions. Automation *abuse,* or the automation of functions by designers and implementation by managers without due regard for the consequences for human performance, tends to define the operator's roles as by-products of the automation. Automation abuse can also promote misuse and disuse of automation by human operators. Understanding the factors associated with each of these aspects of human use of automation can lead to improved system design, effective training methods, and judicious policies and procedures involving automation use.

## INTRODUCTION

The revolution ushered in by the digital computer in the latter half of this century has fundamentally changed many characteristics of work, leisure, travel, and other human activities. Even more radical changes are anticipated in the next century as computers increase in power, speed, and "intelligence." These factors sustain much of the drive toward automation in the workplace and elsewhere, as more capable computer hardware and software become available at low cost.

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Technical issues—how automation functions are implemented and the characteristics of the associated sensors, controls, and software—dominate most writing on automation technology. This is not surprising, given the sophistication and ingenuity of design of many such systems (e.g., automatic landing of an aircraft). The economic benefits that automation can provide, or is perceived to offer, also tend to focus public attention on the technical capabilities of automation, which have been amply documented in such diverse domains as aviation (Spitzer, 1987), automobiles (IVHS America, 1992), manufacturing (Bessant, Levy, Ley, Smith, & Tranfield, 1992), medicine (Thompson, 1994), robotics

(Sheridan, 1992), and shipping (Grabowski & Wallace, 1993).

Humans work with and are considered essential to all of these systems. However, in comparison with technical capabilities, human capabilities—human performance and cognition in automated systems—are much less frequently written about or discussed in public forums. This stems not from a relative lack of knowledge (Bainbridge, 1983; Billings, 1991; Chambers & Nagel, 1985; Hopkin, 1995; Mouloua & Parasuraman, 1994; Parasuraman & Mouloua, 1996; Rasmussen, 1986; Riley, 1995; Sheridan, 1992; Wickens, 1994; Wiener & Curry, 1980; Woods, 1996) but, rather, from a much greater collective emphasis on the technological than on the human aspects of automation.

In this paper we examine human performance aspects of the technological revolution known as automation. We analyze the factors influencing human use of automation in domains such as aviation, manufacturing, ground transportation, and medicine, though our treatment does not focus on any one of these systems. Consideration of these factors is important not only to systems currently under development, such as automation tools for air traffic management (Erzberger, 1992), but also to far-reaching system concepts that may be implemented in the future, such as "free flight" (Planzer & Hoffman, 1995; Radio and Technical Committee on Aeronautics, 1995).

A prevalent assumption about automation is that it resides in tyrannical machines that replace humans, a view made popular by Chaplin in his movie *Modern Times*. However, it has become evident that automation does not supplant human activity; rather, it changes the nature of the work that humans do, often in ways unintended and unanticipated by the designers of automation. In modern times, humans are *consumers* of automation. We discuss the human usage patterns of automation in this paper.

First, however, some restrictions of scope should be noted. We focus on the influence of automation on individual task performance. We do not consider in any detail the impact of automation on team (Bowers, Oser, Salas, & Cannon-Bowers, 1996) or job performance (Smith & Carayon, 1995) or on organizational behavior (Gerwin & Leung, 1986; Sun & Riis, 1994). We also do not examine the wider sociological, sociopsychological, or sociopolitical aspects of automation and human behavior (Sheridan, 1980; Zuboff, 1988), though such issues are becoming increasingly important to consider in automation design (Hancock, 1996; Nickerson, 1995).

### *What Is Automation?*

We define *automation* as the execution by a machine agent (usually a computer) of a function that was previously carried out by a human. What is considered automation will therefore change with time. When the reallocation of a function from human to machine is complete and permanent, then the function will tend to be seen simply as a machine operation, not as automation. Examples of this include starter motors for cars and automatic elevators. By the same token, such devices as automatic teller machines, cruise controls in cars, and the flight management system (FMS) in aircraft qualify as automation because they perform functions that are also performed manually by humans. Today's automation could well be tomorrow's machine.

Automation of physical functions has freed humans from many time-consuming and labor-intensive activities; however, full automation of cognitive functions such as decision making, planning, and creative thinking remains rare. Could machine displacement of human thinking become more commonplace in the future? In principle, this might be possible. For example, devices such as optical disks are increasingly replacing books as repositories of large amounts of information. Evolutionary neurobiologists have speculated that external means of storing information and knowledge (as opposed to internal storage in the human brain) not only have played an important role in the evolution of human consciousness but will also do so in its future development (Donald, 1991). Hence permanent allocation of higher cognitive functions to machines need not be conceptually problematic. Moreover, such a transfer will probably not replace but, rather, will modify human thinking. In practice, however, despite more than three decades of research on artificial intelligence, neural networks, and the development, in Schank's (1984) terms, of the "cognitive computer," enduring transfer of thinking skills to machines has proven very difficult.

Automation can be usefully characterized by a continuum of levels rather than as an all-or-none concept (McDaniel, 1988; Riley, 1989; Sheridan, 1980). Under full manual control, a particular function is controlled by the human, with no machine control. At the other extreme of full automation, the machine controls all aspects of the function, including its monitoring, and only its products (not its internal operations) are visible to the human operator.

Different levels of automation can be identified between these extremes. For example, Sheridan (1980) identified 10 such levels of automation; in his seventh level, the automation carries out a function and informs the operator to that effect, but the operator cannot control the output. Riley (1989) defined automation levels as the combination of particular values along two dimensions: "intelligence" and autonomy. Automation with high autonomy can carry out functions only with initiating input from the operator. At the highest levels, the functions cannot be overridden by the human operator (e.g., the flight envelope protection function of the Airbus 320 aircraft).

### *Human Roles in Automated Systems*

Until recently, the primary criteria for applying automation were technological feasibility and cost. To the extent that automation could perform a function more efficiently, reliably, or accurately than the human operator, or merely replace the operator at a lower cost, automation has been applied at the highest level possible. Technical capability and low cost are valid reasons for automation if there is no detrimental impact on human (and hence system) performance in the resulting system. As we discuss later, however, this is not always the case. In the ultimate extension of this practice, automation would completely replace operators in systems. Automation has occasionally had this effect (e.g., in some sectors of the manufacturing industry), but more generally automation has not completely displaced human workers. Although in lay terms it is easiest to think of an automated system as not including a human, most such systems, including "unmanned" systems such as spacecraft, involve human operators in a supervisory or monitoring role.

One of the considerations preventing the total removal of human operators from such systems has been the common perception that humans are more flexible, adaptable, and creative than automation and thus are better able to respond to changing or unforeseen conditions. In a sense, then, one might consider the levels of automation and operator involvement that are permitted in a system design as reflecting the relative levels of trust in the designer on one hand and the operator on the other. Given that no designer of automation can foresee all possibilities in a complex environment, one approach is to rely on the human operator to exercise his or her experience and judgment in using automation. Usually (but not always) the operator is given override authority and some discretion regarding the use of automation.

This approach, however, tends to define the human operator's roles and responsibilities in terms of the automation (Riley, 1995). Designers tend to automate everything that leads to an economic benefit and leave the operator to manage the resulting system. Several important human factors issues emerge from this approach, including consequences of inadequate feedback about the automation's actions and intentions (Norman, 1990), awareness and management of automation modes (Sarter & Woods, 1994), underreliance on automation (Sorkin, 1988), and overreliance on automation (Parasuraman, Molloy, & Singh, 1993; Riley, 1994b). An extensive list of human factors concerns associated with cockpit automation was recently compiled by Funk, Lyall, and Riley (1995).

*Incidents and Accidents*

Unfortunately, the ability to address human performance issues systematically in design and training has lagged behind the application of automation, and issues have come to light as a result of accidents and incidents. The need for better feedback about the automation's state was revealed in a number of "controlled flight into terrain" aircraft accidents, in which the crew selected the wrong guidance mode, and indications presented to the crew appeared similar to when the system was tracking the glide slope perfectly (Corwin, Funk, Levitan, & Bloomfield, 1993). The difficulty of managing complex flight guidance modes and maintaining awareness of which mode the aircraft was in was demonstrated by accidents attributed to pilot confusion regarding the current mode (Sarter & Woods, 1994). For example, an Airbus A320 crashed in Strasbourg, France, when the crew apparently confused the vertical speed and flight path angle modes (Ministere de l'Equipement, des Transports et du Tourisme, 1993).

Underreliance on automation was demonstrated in railroad accidents in which crews chose to neglect speed constraints and their associated alerts. Even after one such accident near Baltimore in 1987, inspectors found that the train operators were continuing to tape over the buzzers that warned them of speed violations (Sorkin, 1988). Finally, overreliance on automation was a contributing cause in an accident near Columbus, Ohio, in 1994. A pilot who demonstrated low confidence in his own manual control skills and tended to rely heavily on the automatic pilot during nighttime, low-visibility approaches failed to monitor the aircraft's airspeed during final approach in a nighttime snowstorm and crashed short of the runway (National Transportation Safety Board [NTSB], 1994).

Most such accidents result from multiple causes, and it can be difficult to untangle the various contributing factors. Whenever automation is involved in an accident, the issue of how the operator used that automation is of interest, but it may be difficult to say that the operator used the automation too much, too little, or otherwise inappropriately. Often the best one can do is to conclude that, the operator having used the automation in a certain way, certain consequences followed. The lessons learned from these consequences then join the growing body of lessons related to automation design and use. In most cases the operator is not clearly wrong in using or not using the automation. Having determined that the operator must be trusted to apply experience and judgment in unforeseen circumstances, he or she is granted the authority to decide when and how to use it (though management may limit this authority to a greater or lesser extent).

This brings up the question of how operators make decisions to use automation. How do they decide whether or not to use automation? Do they make these decisions rationally or based on nonrational factors? Are automation usage decisions appropriate given the relative performances of operator and automation? When and why do people misuse automation?

*Overview*

In this paper we examine the factors influencing the use, misuse, disuse, and abuse of automation. Two points should be emphasized regarding our terminology. First, we include in our discussion of human use of automation not only human operators of systems but also designers, supervisors, managers, and regulators. This necessarily means that any human error associated with use of automation can include the human operator, the designer, or even management error; examples of each are provided throughout this paper.

Second, in using terms such as *misuse, disuse,* and *abuse,* no pejorative intent is implied toward any of these groups. We define *misuse* as overreliance on automation (e.g., using it when it should not be used, failing to monitor it effectively), *disuse* as underutilization of automation (e.g., ignoring or turning off automated alarms or safety systems), and *abuse* as inappropriate application of automation by designers or managers (e.g., automation that fails to consider the consequences for human performance in the resulting system).

## USE OF AUTOMATION

The catastrophic accidents in Strasbourg, Baltimore, and elsewhere are a powerful reminder that the decision to use (or not to use) automation can be one of the most important decisions a human operator can make, particularly in time-critical situations. What factors influence this decision? Several authors (Lee & Moray, 1992; Muir, 1988) have suggested that automation reliability and the operator's trust in automation are major factors. Riley (1989) examined several other factors that might also influence automation use decisions, including how much workload the operator was experiencing and how much risk was involved in the situation. He proposed that automation usage was a complex, interactive function of these and other factors. Others (McClumpha & James, 1994; Singh, Molloy, & Parasuraman, 1993a, 1993b) have suggested that operator attitudes toward automation might influence automation usage. We discuss the impact of each of these factors.

### *Attitudes Toward Automation*

It is easy to think of examples in which automation usage and attitudes toward automation are correlated. Often these attitudes are shaped by the reliability or accuracy of the automation. For example, automatic braking systems are particularly helpful when driving on wet or icy roads, and drivers who use these systems have favorable attitudes toward them. Smoke detectors are prone to false alarms, however, and are disliked by many people, some of whom might disable them. In either case, automation use (or lack of use) reflects perceived reliability. In other instances, attitudes may not be so closely linked to automation reliability. For example, many elderly people tend not to use automatic teller machines because of a generally negative attitude toward computer technology and a more positive attitude toward social interaction with other humans (bank tellers). There are also people who prefer not to use automatic brakes, and some people like smoke alarms.

Attitudes toward automation vary widely among individuals (Helmreich, 1984; McClumpha & James, 1994; Singh, Deaton, & Parasuraman, 1993). Understanding these attitudes—positive and negative, general and specific—constitutes a first step toward understanding human use of automation.

Wiener (1985, 1989) queried pilots of automated aircraft about their attitudes toward different cockpit systems. A notable finding was that only a minority of the pilots agreed with the statement, "automation reduces workload." In fact, a substantial minority of the pilots thought that automation had increased their workload. Later studies revealed that a major source of the increased workload was the requirement to reprogram automated systems such as the FMS when conditions changed (e.g., having to land at a different runway than originally planned). Thus many pilots felt that automation increased workload precisely at the time when it was needed most—that is, during the high-workload phase of descent and final approach. Subsequent, more formal questionnaire studies have also revealed substantial individual differences in pilot attitudes toward cockpit automation (McClumpha & James, 1994; Singh et al., 1993a).

Beliefs and attitudes are not necessarily linked to behaviors that are consistent with those attitudes. To what extent are individual attitudes toward automation consistent with usage patterns of automation? The issue remains to be explored fully. In the case of a positive view of automation, attitudes and usage may be correlated. Examples include the horizontal situation indicator, which pilots use for navigation and find extremely helpful, and automatic hand-offs between airspace sectors, which air traffic controllers find useful in reducing their workload.

More generally, attitudes may not necessarily be reflected in behavior. Two recent studies found no relationship between attitudes toward automation and actual reliance on automation during multiple-task performance (Riley, 1994a, 1996; Singh et al., 1993b). Furthermore, there may be differences between general attitudes toward automation (i.e., all automation) and domain-specific attitudes (e.g., cockpit automation). For all these reasons it may be difficult to predict automation usage patterns on the basis of questionnaire data alone. Performance data on actual human operator usage of automation are needed. We now turn to such evidence.

*Mental Workload*

One of the fundamental reasons for introducing automation into complex systems is to lessen the chance of human error by reducing the operator's high mental workload. However, this does not always occur (Edwards, 1977; Wiener, 1988). Nevertheless, one might argue that an operator is more likely to choose to use automation when his or her workload is high than when it is low or moderate. Surprisingly, there is little evidence in favor of this assertion. Riley (1994a) had college students carry out a simple step-tracking task and a character classification task that could be automated. He found that manipulating the difficulty of the tracking task had no impact on the students' choice to use automation in the classification task. The overall level of automation usage in this group was quite low—less than about 50%. A possible reason could be that these young adults typically prefer manual over automated control, as reflected in their interest in computer video games that require high levels of manual skill. However, in a replication study carried out with pilots, who turned on the automation much more frequently, no relationship between task difficulty and automation usage was found.

The difficulty manipulation used by Riley (1994a) may have been insufficient to raise workload significantly, given that task performance was only slightly affected. Moreover, the participants had to perform only two simple, discrete-trial, artificial tasks. Perhaps task difficulty manipulations affect automation usage only in a multitask environment with dynamic tasks resembling those found in real work settings. Harris, Hancock, and Arthur (1993) used three flight tasks—tracking, system monitoring, and fuel management—and gave participants the option of automating the tracking task. Following advance notice of an increase in task difficulty, there was a trend toward use of automation as a workload management strategy. However, individual variability in automation usage patterns obscured any significant relationship between task load increase and automation usage.

The evidence concerning the influence of task load on automation usage is thus unclear. Nevertheless, human operators often cite excessive workload as a factor in their choice of automation. Riley, Lyall, and Wiener (1993) reported that workload was cited as one of two most important factors (the other was the urgency of the situation) in pilots' choice of such automation as the autopilot, FMS, and flight director during simulated flight. However, these data also showed substantial individual differences. Pilots were asked how often, in actual line performance, various factors influenced their automation use decisions. For most factors examined, many pilots indicated that a particular factor rarely influenced their decision, whereas an almost equal number said that the same factor influenced their decisions quite often; very few gave an answer in the middle.

Studies of human use of automation typically find large individual differences. Riley (1994a) found that the patterns of automation use differed markedly between those who cited fatigue as an influence and those who cited other factors. Moreover, there were substantial differences between students and pilots, even though the task domain was artificial and had no relation to aviation. Within both pilot and student groups were strong differences among individuals in automation use. These results suggest that different people employ different strategies when making automation use decisions and are influenced by different considerations.

Subjective perceptions and objective measurement of performance are often dissociated (Yeh & Wickens, 1988). Furthermore, the nature of workload in real work settings can be fundamentally different from workload in most laboratory tasks. For example, pilots are often faced with deciding whether to fly a clearance (from air traffic control) through the FMS, through simple heading or altitude changes on the glareshield panel, or through manual control. Casner (1994) found that pilots appear to consider the predictability of the flight path and the demands of other tasks in reaching their decision. When the flight path is highly predictable, overall workload may be reduced by accepting the higher short-term workload associated with programming the FMS, whereas when the future flight path is more uncertain, such a workload investment may not be warranted. To fully explore the implications of workload on automation use, the workload attributes of particular systems of interest should be better represented; in the flight deck, this would include a trade-off between short-term and long-term workload investments.

*Cognitive Overhead*

In addition to the workload associated with the operator's other tasks, a related form of workload—that associated with the decision to use the automation itself—may also influence automation use. Automation usage decisions may be relatively straightforward if the advantages of using the automation are clear cut. When the benefit offered by automation is not readily apparent, however, or if the benefit becomes clear only after much thought and evaluation, then the cognitive "overhead" involved may persuade the operator not to use the automation (Kirlik, 1993).

Overhead can be a significant factor even for routine actions for which the advantages of automation are clear—for example, entering text from a sheet of paper into a word processor. One choice, a labor-intensive one, is to enter the text manually with a keyboard. Alternatively, a scanner and an optical character recognition (OCR) program can be used to enter the text into the word processor. Even though modern OCR programs are quite accurate for clearly typed text, most people would probably choose not to use this form of automation because the time involved in setting up the automation and correcting errors may be perceived as not worth the effort. (Only if several sheets of paper had to be converted would the OCR option be considered.)

Cognitive overhead may be important with high-level automation that provides the human operator with a solution to a complex problem. Because these aids are generally used in uncertain, probabilistic environments, the automated solution may or may not be better than a manual one. As a result, the human operator may expend considerable cognitive resources in generating a manual solution to the problem, comparing it with the automated solution, and then picking one of the solutions. If the operator perceives that the advantage offered by the automation is not sufficient to overcome the cognitive overhead involved, then he or she may simply choose not to use the automation and do the task manually.

Kirlik (1993) provided empirical evidence of this phenomenon in a dual-task study in which an autopilot was available to participants for a primary flight task. He found that none of the participants used the automation as intended—that is, as a task-shedding device to allow attention to be focused on the secondary task when it was present, but not otherwise. Kirlik (1993) hypothesized that factors such as an individual's manual control skills, the time needed to engage the autopilot, and the cost of delaying the secondary task while engaging the autopilot may have influenced automation use patterns. Using a Markov modeling analysis to identify the optimal strategies of automation use given each of these factors, he found that conditions exist for which the optimal choice is *not* to use the automation.

*Trust*

Trust often determines automation usage. Operators may not use a reliable automated system if they believe it to be untrustworthy. Conversely, they may continue to rely on automation even when it malfunctions. Muir (1988) argued that individuals' trust for machines can be affected by the same factors that influence trust between individuals; for example, people trust others if they are reliable and honest, but they lose trust when they are let down or betrayed, and the subsequent redevelopment of trust takes time. She found that use of an automated aid to control a simulated soft drink manufacturing plant was correlated with a simple subjective measure of trust in that aid.

Using a similar process control simulation, Lee and Moray (1992) also found a correlation between automation reliance and subjective trust, although their participants also tended to be biased toward manual control and showed "inertia" in their allocation policy. In a subsequent study, Lee and Moray (1994) found that participants chose manual control if their confidence in their own ability to control the plant exceeded their trust of the automation and that they otherwise chose automation.

A factor in the development of trust is automation reliability. Several studies have shown that operators' use of automation reflects automation reliability, though occasional failures of automation do not seem to be a deterrent to future use of the automation. Riley (1994a) found that college students and pilots did not delay turning on automation after recovery from a failure; in fact, many participants continued to rely on the automation during the failure. Parasuraman et al. (1993) found that even after the simulated catastrophic failure of an automated engine-monitoring system, participants continued to rely on the automation for some time, though to a lesser extent than when the automation was more reliable.

These findings are surprising in view of earlier studies suggesting that operator trust in automation is slow to recover following a failure of the automation (Lee & Moray, 1992). Several possible mitigating factors could account for the discrepancy.

First, if automation reliability is relatively high, then operators may come to rely on the automation, so that occasional failures do not substantially reduce trust in the automation unless the failures are sustained. A second factor may be the ease with which automation behaviors and state indicators can be detected (Molloy & Parasuraman, 1994). As discussed earlier, the overhead involved in enabling or disengaging automation may be another factor. Finally, the overall complexity of the task may be relevant; complex task domains may prompt different participants to adopt different task performance strategies, and operator use of automation may be influenced by these task performance strategies as well as by factors directly related to the automation.

### *Confidence, Risk, and Other Factors*

Several other factors are probably also important in influencing the choice to use or not to use automation. Some of these factors may have a direct influence, whereas others may interact with the factors already discussed. For example, the influence of cognitive overhead may be particularly evident if the operator's workload is already high. Under such circumstances, operators may be reluctant to use automation even if it is reliable, accurate, and generally trustworthy. Lee and Moray (1992) and Riley (1994a) also identified self-confidence in one's manual skills as an important factor in automation usage. If trust in automation is greater than self-confidence, automation would be engaged, but not otherwise.

Riley (1994a) suggested that this interaction could be moderated by other factors, such as the risk associated with the decision to use or not to use automation. He outlined a model of automation usage based on a number of factors (see Figure 1). The factors for which he found support include automation reliability, trust in the automation, self-confidence in one's own capabilities, task complexity, risk, learning about automation states, and fatigue. However, he did not find that self-confidence was necessarily justified; participants in his studies were not able to accurately assess their own performance and use the automation accordingly, again showing the dissociation between subjective estimates and performance mentioned earlier. Furthermore, large individual differences were found in almost all aspects of automation use decisions. This can make systematic prediction of automation usage by individuals difficult, much as the prediction of human error is problematic even when the factors that give rise to errors are understood (Reason, 1990).

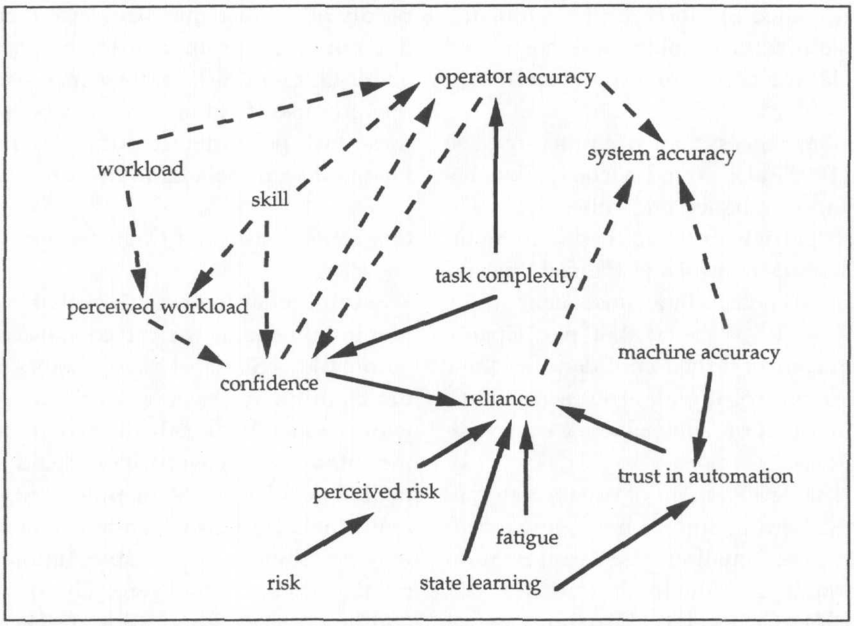


*Figure 1.* Interactions between factors influencing automation use. Solid arrows represent relationships supported by experimental data; dotted arrows are hypothesized relationships or relationships that depend on the system in question. Reproduced from Parasuraman & Mouloua (1996) with permission from Lawrence Erlbaum Associates.

### *Practical Implications*

These results suggest that automation use decisions are based on a complex interaction of many factors and are subject to strongly divergent individual considerations. Although many of the factors have been examined and the most important identified, predicting the automation use of an individual based on knowledge of these factors remains a difficult prospect. Given this conclusion, in a human-centered automation philosophy, the decision to use or not to use automation is left to the operator (within limits set by management). Having granted the operator this discretion, designers and operators should recognize the essential unpredictability of how people will use automation in specific circumstances, if for no other reason than the presence of these individual differences.

If automation is to be used appropriately, potential biases and influences on this decision should be recognized by training personnel, developers, and managers. Individual operators should be made aware of the biases they may bring to the use of automation. For example, if an individual is more likely to rely on automation when tired, he or she should be made aware that fatigue may lead to overreliance and be taught to recognize the implications of that potential bias. Finally, policies and procedures may profitably highlight the importance of taking specific considerations into account when deciding whether or not to use automation, rather than leaving that decision vulnerable to biases and other factors that might produce suboptimal strategies.

## MISUSE OF AUTOMATION

Most automated systems are reliable and usually work as advertised. Unfortunately, some may fail or behave unpredictably. Because such occurrences are infrequent, however, people will come to trust the automation. However, can there be too much trust? Just as mistrust can lead to disuse of alerting systems, excessive trust can lead operators to rely uncritically on automation without recognizing its limitations or fail to monitor the automation's behavior. Inadequate monitoring of automated systems has been implicated in several aviation incidents—for instance, the crash of Eastern Flight 401 in the Florida Everglades. The crew failed to notice the disengagement of the autopilot and did not monitor their altitude while they were busy diagnosing a possible problem with the landing gear (NTSB, 1973). Numerous other incidents and accidents since this crash testify to the potential for human operators' overreliance on automation.

*Overreliance on Automation*

The Air Transport Association (ATA, 1989) and Federal Aviation Administration (FAA, 1990) have expressed concern about the potential reluctance of pilots to take over from automated systems. In a dual-task study, Riley (1994b) found that although almost all students turned the automation off when it failed, almost half the pilots did not, even though performance on the task was substantially degraded by the failed automation and the participants were competing for awards based on performance. Even though the task had no relation to aviation, pilots showed significantly more reliance on automation than did students in all conditions. However, the fact that almost half the pilots used the automation when it failed, whereas the rest turned it off, is further evidence of marked individual differences in automation use decisions.

Overreliance on automation represents an aspect of misuse that can result from several forms of human error, including decision biases and failures of monitoring. It is not only untrained operators who show these tendencies. Will (1991) found that skilled subject matter experts had misplaced faith in the accuracy of diagnostic expert systems (see also Weick, 1988). The Aviation Safety Reporting System (ASRS) also contains many reports from pilots that mention monitoring failures linked to excessive trust in or overreliance on automated systems such as the autopilot or FMS (Mosier, Skitka, & Korte, 1994; Singh et al., 1993a, 1993b).

*Decision Biases*

Human decision makers exhibit a variety of biases in reaching decisions under uncertainty (e.g., underestimating the influence of the base rate or being overconfident in their decisions). Many of these biases stem from the use of decision heuristics (Tversky & Kahneman, 1984) that people use routinely as a strategy to reduce the cognitive effort involved in solving a problem (Wickens, 1992). For example, Tversky and Kahneman (1984) showed that even expert decision makers use the heuristic of representativeness in making decisions. This can lead to errors when a particular event or symptom is highly representative of a particular condition but highly unlikely for other reasons (e.g., a low base rate). Although heuristics are a useful alternative to analytical or normative methods (e.g., utility theory or Bayesian statistics) and generally lead to successful decision making, they can result in biases that lead to substandard decision performance.

Automated systems that provide decision support may reinforce the human tendency to use heuristics and the susceptibility to automation bias (Mosier & Skitka, 1996). Although reliance on automation as a heuristic may be an effective strategy in many cases, overreliance can lead to errors, as is the case with any decision heuristic. Automation bias may result in omission errors, in which the operator fails to notice a problem or take an action because the automated aid fails to inform the operator. Such errors include monitoring failures, which are discussed in more detail later. Commission errors occur when operators follow an automated directive that is inappropriate.

Mosier and Skitka (1996) also pointed out that reliance on the decisions of automation can make humans less attentive to contradictory sources of evidence. In a part-task simulation study, Mosier, Heers, Skitka, and Burdick (1996) reported that pilots tended to use automated cues as a heuristic replacement for information seeking. They found that pilots tended not to use disconfirming evidence available from cockpit displays when there was a conflict between expected and actual automation performance. Automation bias error rates were also found to be similar for student and professional pilot samples, indicating that expertise does not guarantee immunity from this bias (Mosier, Skitka, Burdick, & Heers, 1996).

*Human Monitoring Errors*

Automation bias represents a case of inappropriate decision making linked to overreliance on automation. In addition, operators may not sufficiently monitor the inputs to automated systems in order to reach effective decisions should the automation malfunction or fail. It is often pointed out that humans do not make good monitors. In fact, human monitoring can be very efficient. For example, in a high-fidelity simulation study of air traffic control, Hilburn, Jorna, and Parasuraman (1995) found that compared with unaided performance, experienced controllers using an automated descent advisor were quicker to respond to secondary malfunctions (pilots not replying to data-linked clearances).

Monitoring in other environments, such as intensive care units and process control, is also generally efficient (Parasuraman, Mouloua, Molloy, & Hilburn, 1996). When the number of *opportunities* for failure is considered—virtually every minute for these continuous, 24-h systems—then the relatively low frequency of monitoring errors is striking. As Reason (1990) pointed out, the opportunity ratio for skill-based and rule-based errors is relatively low. The absolute number of errors may be high, however, and the application of increased levels of automation in these systems creates more opportunities for failures of monitoring as the number of automated subsystems, alarms, decision aids, and so on increase.

McClellan (1994) discussed pilot monitoring for various types of autopilot failures in aircraft. FAA certification of an autopilot requires detection of "hard-over," uncommanded banks (up to a maximum of 60°) within 3 s during test flight. Although such autopilot failures are relatively easy to detect because they are so salient, "slow-over" rolls, in which the autopilot rolls the aircraft gradually and smoothly, are much less salient and can go undetected until the aircraft wings are nearly vertical (e.g., the 1985 China Airlines incident; NTSB, 1986). McClellan pointed out that autopilot failures, though infrequent, do occur and that incidents and accidents can be avoided not only by appropriate certification but also by training:

> All autopilot certification theory and testing is based on the human pilot identifying an autopilot failure and promptly disabling the autopilot. . . . It may not always be easy to quickly identify an actual autopilot failure, because a malfunction could manifest itself in various ways. Instead of taking time to troubleshoot an autopilot failure, [pilots] must treat every unexpected maneuver when the autopilot is engaged as a failure and immediately disable the autopilot and trim system. (P. 80)

Although poor monitoring can have multiple determinants, operator overreliance on automation may be an important contributor. Mosier et al. (1994) found that 77% of ASRS incidents in which overreliance on automation was suspected involved a probable failure in monitoring. Similar incidents have occurred elsewhere. For example, a satellite-based navigational system failed "silently" in a cruise ship that ran aground off Nantucket Island. The crew did not monitor other sources of position information that would have indicated that they had drifted off course (National Transportation Safety Board, 1997b).

*Manual task load.* Parasuraman and colleagues (1993, 1994) have examined the factors influencing monitoring of automation and found that the overall task load imposed on the operator, which determined the operator's attention strategies, is an important factor. In their studies, participants simultaneously performed tracking and fuel management tasks manually and had to monitor an automated engine status task. Participants were required to detect occasional automation failures by identifying engine malfunctions not detected by the automation. In the constant reliability condition, automation reliability was invariant over time, whereas in the variable reliability condition, automation reliability varied from low to high every 10 min. Participants detected more than 70% of malfunctions on the engine status task when they performed the task manually while simultaneously carrying out tracking and fuel management. However, when the engine status task was under automation control, detection of malfunctions was markedly reduced in the constant reliability condition.

In a separate experiment, the same conditions were administered, but participants performed only the monitoring task without the tracking and fuel management tasks. Individuals were now nearly perfect (> 95%) in detecting failures in the automated control of the engine status task, which was the only task. These results point to the potential cost of long-term automation on system performance and show that operators can be poor at monitoring automation when they have to perform other manual tasks simultaneously. Other studies have shown that poor automation monitoring is exhibited by pilots as well as nonpilots (Parasuraman et al., 1994) and also when only a single automation failure occurs during the simulation (Molloy & Parasuraman, 1996).

*Automation reliability and consistency.* The monitoring performance of participants in these studies supports the view that reliable automation engenders trust (Lee & Moray, 1992). This leads to a reliance on automation that is associated with only occasional monitoring of its efficiency, suggesting that a critical factor in the development of this phenomenon might be the constant, unchanging reliability of the automation.

Conversely, automation with inconsistent reliability should not induce trust and should therefore be monitored more closely. This prediction was supported by the Parasuraman et al. (1993) finding that monitoring performance was significantly higher in the variable reliability condition than in the constant reliability condition (see Figure 2). The absolute level of automation reliability may also affect monitoring performance. May, Molloy, and Parasuraman (1993) found that the detection rate of automation failures varied inversely with automation reliability.

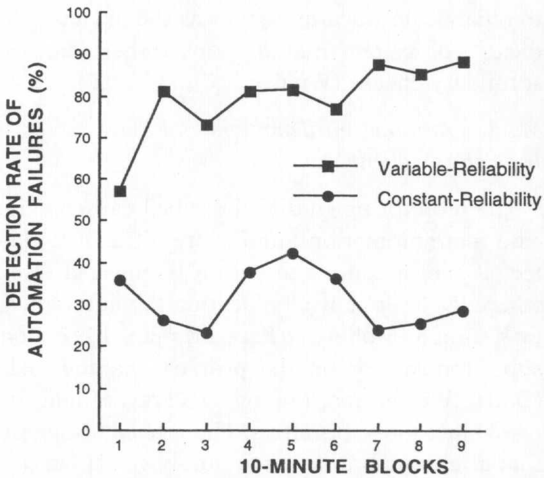


*Figure 2.* Effects of consistency of automation reliability (constant or variable) on monitoring performance under automation. Based on data from Parasuraman et al. (1993).

### *Machine Monitoring*

Can the problem of poor human monitoring of automation itself be mitigated by automation? Some monitoring tasks can be automated, such as automated checklists for preflight procedures (e.g., Palmer & Degani, 1991), though this may merely create another system that the operator must monitor. Pattern recognition methods, including those based on neural networks, can also be used for machine detection of abnormal conditions (e.g., Gonzalez & Howington, 1977). Machine monitoring may be an effective design strategy in some instances, especially for lower-level functions, and is used extensively in many systems, particularly process control.

However, automated monitoring may not provide a general solution to the monitoring problem, for at least two reasons. First, automated monitors can increase the number of alarms, which is already high in many settings. Second, to protect against failure of automated monitors, designers may be tempted to put in another system that monitors the automated monitor, a process that could lead to infinite regress. These high-level monitors can fail also, sometimes silently. Automated warning systems can also lead to reliance on warning signals as the primary indicator of system malfunctions rather than as secondary checks (Wiener & Curry, 1980).

### *Making Automation Behaviors and State Indicators Salient*

The monitoring studies described earlier indicate that automation failures are difficult to detect if the operator's attention is engaged elsewhere. Neither centrally locating the automated task (Singh, Molloy, & Parasuraman, 1997) nor superimposing it on the primary manual task (Duley, Westerman, Molloy, & Parasuraman, in press) mitigates this effect. These results suggest that attentional rather than purely visual factors (e.g., nonfoveal vision) underlie poor monitoring. Therefore, making automation state indicators more salient may enhance monitoring.

One possibility is to use display integration to reduce the attentional demands associated with detecting a malfunction in an automated task. Integration of elements within a display is one method for reducing attentional demands of fault detection, particularly if the integrated components combine to form an emergent feature such as an object or part of an object (Bennett & Flach, 1992; Woods, Wise, & Hanes, 1981). If the emergent feature is used to index a malfunction, detection of the malfunction could occur preattentively and in parallel with other tasks.

Molloy and Parasuraman (1994; see also Molloy, Deaton, & Parasuraman, 1995) examined this possibility with a version of an engine status display that is currently implemented in many cockpits: a CRT-based depiction of engine instruments and caution and warning messages. The display consisted of four circular gauges showing different engine parameters. The integrated form of this display was based on one developed by Abbott (1990)—the Engine Monitoring and Crew Alerting System (EMACS)—in which the four engine parameters were shown as columns on a deviation bar graph. Parameter values above or below normal were displayed as deviations from a horizontal line (the emergent feature) representing normal operation.

Pilots and nonpilots were tested with these engine status displays using the same paradigm developed by Parasuraman et al. (1993). In the manual condition, participants were responsible for identifying and correcting engine malfunctions. Performance (detection rate) under manual conditions was initially equated for the baseline and EMACS tasks. In the automated condition, a system routine detected malfunctions without the need for operator intervention; however, from time to time the automation routine failed to detect malfunctions, which the participants were then required to manage. Although participants detected only about a third of the automation failures with the nonintegrated baseline display, they detected twice as many failures with the integrated EMACS display.

Adaptive task allocation may provide another means of making automation behaviors more salient by refreshing the operator's memory of the automated task (Lewandowsky & Nikolic, 1995; Parasuraman, Bahri, Deaton, Morrison, & Barnes, 1992). The traditional approach to automation is based on a policy of allocation of function in which either the human or the machine has full control of a task (Fitts, 1951). An alternative philosophy, variously termed *adaptive task allocation* or *adaptive automation,* sees function allocation between humans and machines as flexible (Hancock & Chignell, 1989; Rouse, 1988; Scerbo, 1996). For example, the operator can actively control a process during moderate workload, allocate this function to an automated subsystem during peak workload if necessary, and retake manual control when workload diminishes. This suggests that one method of improving monitoring of automation might be to insert brief periods of manual task performance after a long period of automation and then to return the task to automation (Byrne & Parasuraman, 1996; Parasuraman, 1993).

Parasuraman, Mouloua, and Molloy (1996) tested this idea using the same flight simulation task developed by Parasuraman et al. (1993). They found that after a 40-min period of automation, a 10-min period in which the task was reallocated to the operator had a beneficial impact on subsequent operator monitoring under automation. Similar results were obtained in a subsequent study in which experienced pilots served as participants (Parasuraman et al., 1994). These results encourage further research into adaptive systems (see Scerbo, 1996, for a comprehensive review). However, such systems may suffer from the same problems as traditional automation if implemented from a purely technology-driven approach, without considering user needs and capabilities (Billings & Woods, 1994).

Display techniques that afford "direct" perception of system states (Vicente & Rasmussen, 1990) may also improve the saliency of automation states and provide better feedback about the automation to the operator, which may in turn reduce overreliance. Billings (1991) has pointed out the importance of keeping the human operator informed about automated systems. This is clearly desirable, and making automation state indicators salient would achieve this objective. However, literal adherence to this principle (e.g., providing feedback about *all* automated systems, from low-level detectors to high-level decision aids) could lead to an information explosion and increase workload for the operator. We suggest that saliency and feedback would be particularly beneficial for automation that is designed to have relatively high levels of autonomy.

*System Authority and Autonomy*

Excessive trust can be a problem in systems with high-authority automation. The operator who believes that the automation is 100% reliable will be unlikely to monitor inputs to the automation or to second-guess its outputs. In Langer's (1989) terms, the human makes a "premature cognitive commitment," which affects his or her subsequent attitude toward the automation. The autonomy of the automation could be such that the operator has little opportunity to practice the skills involved in performing the automated task manually. If this is the case, then the loss in the operator's own skills relative to the performance of the automation will tend to lead to an even greater reliance on the automation (see Lee & Moray, 1992), creating a vicious circle (Mosier et al., 1994; Satchell, 1993).

Sarter and Woods (1995) proposed that the combination of high authority and autonomy of automation creates multiple "agents," who must work together for effective system performance. Although the electronic copilot (Chambers & Nagel, 1985) is still in the conceptual stage for the cockpit, current cockpit automation possesses many qualities consistent with autonomous, agentlike behavior. Unfortunately, because the properties of the automation can create "strong but silent" partners to the human operator, mutual understanding between machine and human agents can be compromised (Sarter, 1996). This is exemplified by the occurrence of FMS mode errors in advanced cockpits, in which pilots have been found to carry out an action appropriate for one mode of the FMS when, in fact, the FMS was in another mode (Sarter & Woods, 1994).

Overreliance on automated solutions may also reduce situation awareness (Endsley, 1996; Sarter & Woods, 1991; Wickens, 1994). For example, advanced decision aids have been proposed that will provide air traffic controllers with resolution advisories on potential conflicts. Controllers may come to accept the proposed solutions as a matter of routine. This could lead to a reduced understanding of the traffic picture compared with when the solution is generated manually (Hopkin, 1995). Whitfield, Ball, and Ord (1980) reported such a loss of the "mental picture" in controllers, who tended to use automated conflict resolutions under conditions of high workload and time pressure.

*Practical Implications*

Taken together, these results demonstrate that overreliance on automation can and does happen, supporting the concerns expressed by the ATA (1989) and FAA (1990) in their human factors plans. System designers should be aware of the potential for operators to use automation when they probably should not, to be susceptible to decision biases caused by overreliance on automation, to fail to monitor the automation as closely as they should, and to invest more trust in the automation than it may merit. Scenarios that may lead to overreliance on automation should be anticipated and methods developed to counter it.

Some strategies that may help in this regard include ensuring that state indications are salient enough to draw operator attention, requiring some level of active operator involvement in the process (Billings, 1991), and ensuring that the other demands on operator attention do not encourage the operator to ignore the automated processes. Other methods that might be employed to promote better monitoring include the use of display integration and adaptive task allocation.

## DISUSE OF AUTOMATION

Few technologies gain instant acceptance when introduced into the workplace. Human operators may at first dislike and even mistrust a new automated system. As experience is gained with the new system, automation that is reliable and accurate will tend to earn the trust of operators. This has not always been the case with new technology. Early designs of some automated alerting systems, such as the Ground Proximity Warning System (GPWS), were not trusted by pilots because of their propensity for false alarms. When corporate policy or federal regulation mandates the use of automation that is not trusted, operators may resort to "creative disablement" of the device (Satchell, 1993).

Unfortunately, mistrust of alerting systems is widespread in many work settings because of the false alarm problem. These systems are set with a decision threshold or criterion that minimizes the chance of a missed warning while keeping the false alarm rate below some low value. Two important factors that influence the device false alarm rate and, hence, the operator's trust in an automated alerting system are the values of the decision criterion and the base rate of the hazardous condition.

The initial consideration for setting the decision threshold of an automated warning system is the cost of a missed signal versus that of a false alarm. Missed signals (e.g., total engine failure) have a phenomenally high cost, yet their frequency is undoubtedly very low. However, if a system is designed to minimize misses at all costs, then frequent device false alarms may result. A low false alarm rate is necessary for acceptance of warning systems by human operators. Accordingly, setting a strict decision criterion to obtain a low false alarm rate would appear to be good design practice.

However, a very stringent criterion may not provide sufficient advance warning. In an analysis of automobile collision warning systems, Farber and Paley (1993) suggested that too low a false alarm rate may also be undesirable because rear-end collisions occur very infrequently (perhaps once or twice in the lifetime of a driver). If the system never emits a false alarm, then the first time the warning sounds would be just before a crash. Under these conditions, the driver might not respond alertly to such an improbable event. Farber and Paley (1993) speculated that an ideal system would be one that signals a collision-*possible* condition, even though the driver would probably avoid a crash. Although technically a false alarm, this type of information might be construed as a warning aid in allowing improved response to an alarm in a collision-likely situation. Thus all false alarms need not necessarily be harmful. This idea is similar to the concept of a "likelihood-alarm," in which more than the usual two alarm states are used to indicate several possible levels of the dangerous condition, ranging from very unlikely to very certain (Sorkin, Kantowitz, & Kantowitz, 1988).

Setting the decision criterion for a low false alarm rate is insufficient by itself for ensuring high alarm reliability. Despite the best intentions of designers, the availability of the most advanced sensor technology, and the development of sensitive detection algorithms, one fact may conspire to limit the effectiveness of alarms: the low a priori probability or base rate of most hazardous events. If the base rate is low, as it often is for many real events, then the posterior probability of a true alarm—the probability that given an alarm, a hazardous condition exists—can be low even for sensitive warning systems.

Parasuraman, Hancock, and Olofinboba (1997) carried out a Bayesian analysis to examine the dependence of the posterior probability on the base rate for a system with a given detection sensitivity ($d'$). Figure 3 shows a family of curves representing the different posterior probabilities of a true alarm when the decision criterion (β) is varied for a warning system with fixed sensitivity (in this example, $d' = 4.7$). For example, β can be set so that this warning system misses only 1 of every 1000 hazardous events (hit rate = .999) while having a false alarm rate of .0594.

Despite the high hit rate and relatively low false alarm rate, the posterior odds of a true alarm with such a system could be very low. For example, when the a priori probability (base rate) of a hazardous condition is low (say, .001), only 1 in 59 alarms that the system emits represents a true hazardous condition (posterior probability = .0168). It is not surprising, then, that many human operators tend to ignore and turn off alarms—they have cried wolf once too often (Sorkin, 1988). As Figure 3 indicates, reliably high posterior alarm probabilities are guaranteed for only certain combinations of the decision criterion and the base rate.

Even if operators do attend to an alarm, they may be slow to respond when the posterior probability is low. Getty, Swets, Pickett, and Gounthier (1995) tested participants' response to a visual alert while they performed a tracking task. Participants became progressively slower to respond as the posterior probability of a true alarm was reduced from .75 to .25. A case of a prison escape in which the escapee deliberately set off a motion detector alarm, knowing that the guards would be slow to respond, provides a real-life example of this phenomenon (Casey, 1993).

These results indicate that designers of automated alerting systems must take into account

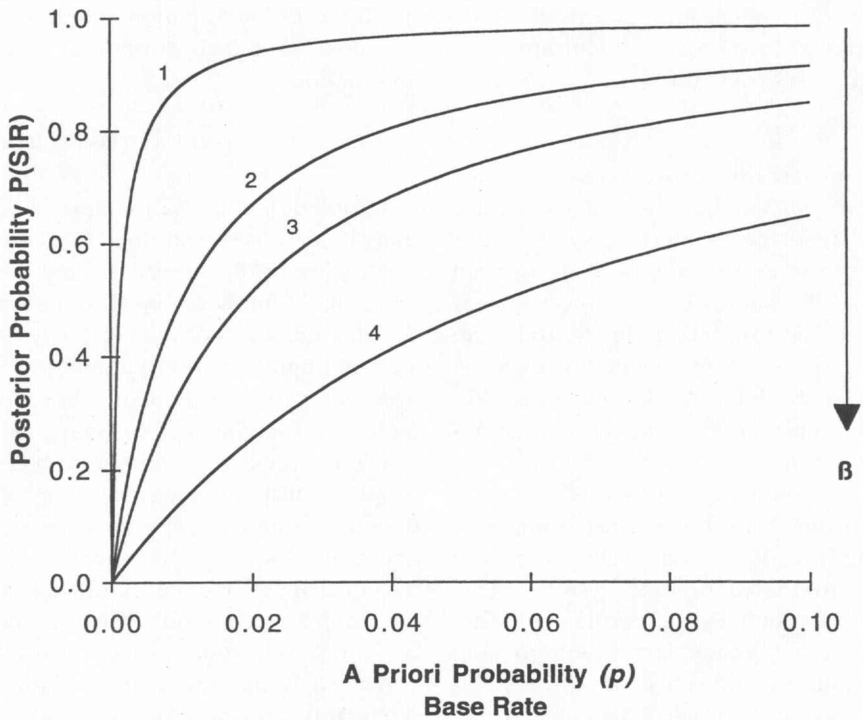


*Figure 3.* Posterior probability (P[S|R]) of a hazardous condition *S* given an alarm response *R* for an automated warning system with fixed sensitivity $d' = 4.7$, plotted as a function of a priori probability (base rate) of *S*. From Parasuraman, Hancock, and Olofinboba (1997). Reprinted with permission of Taylor & Francis.

not only the decision threshold at which these systems are set (Kuchar & Hansman, 1995; Swets, 1992) but also the a priori probabilities of the condition to be detected (Parasuraman, Hancock, et al., 1997). Only then will operators tend to trust and use the system. In many warning systems, designers accept a somewhat high false alarm rate if it ensures a high hit rate. The reason for this is that the costs of a miss can be extremely high, whereas the costs of a false alarm are thought to be much lower.

For example, if a collision avoidance system's decision criterion is set high enough to avoid a large number of false alarms, it may also miss a real event and allow two airplanes to collide. Having set the criterion low enough to ensure that very few real events are missed, the designers must accept a higher expected level of false alarms. Normally this is thought to incur a very low cost (e.g., merely the cost of executing an unnecessary avoidance maneuver), but the consequences of frequent false alarms and consequential loss of trust in the system are often not included in this trade-off.

### *Practical Implications*

The costs of operator disuse because of mistrust of automation can be substantial. Operator disabling or ignoring of alerting systems has played a role in several accidents. In the Conrail accident near Baltimore in 1987, investigators found that the alerting buzzer in the train cab had been taped over. Subsequent investigation showed similar disabling of alerting systems in other cabs, even after prior notification of an inspection was given.

Interestingly, following another recent train accident involving Amtrak and Marc trains near Washington, D.C., there were calls for fitting trains with automated braking systems. This solution seeks to compensate for the possibility that train operators ignore alarms by overriding the operator and bringing a train that is in violation of a speed limit to a halt. This is one of the few instances in which a conscious design decision is made to allow automation to override the human operator, and it reflects, as was suggested earlier, an explicit expression of the relative levels of trust between the human operator and automation. In most cases, this trade-off is decided in favor of the operator; in this case, however, it has been made in favor of automation specifically because the operator has been judged untrustworthy.

Designers of alerting systems must take into account both the decision threshold and the base rate of the hazardous condition in order for operators to trust and use these systems. The costs of unreliable automation may be hidden. If high false alarm rates cause operators not to use a system and disuse results in an accident, system designers or managers determine that the operator was at fault and implement automation to compensate for the operator's failures. The operator may not trust the automation and could attempt to defeat it; the designer or manager does not trust the operator and puts automation in a position of greater authority. This cycle of operator distrust of automation and designer or manager distrust of the operator may lead to abuse of automation.

## ABUSE OF AUTOMATION

Automation abuse is the automation of functions by designers and implementation by managers without due regard for the consequences for human (and hence system) performance and the operator's authority over the system. The design and application of automation, whether in aviation or in other domains, has typically been technology centered. Automation is applied where it provides an economic benefit by performing a task more accurately or more reliably than the human operator or by replacing the operator at a lower cost. As mentioned previously, technical and economic factors are valid reasons for automation, but only if human performance in the resulting system is not adversely affected.

When automation is applied for reasons of safety, it is often because a particular incident or accident identifies cases in which human error was seen to be a major contributing factor. Designers attempt to remove the source of error by automating functions carried out by the human operator. The design questions revolve around the hardware and software capabilities required to achieve machine control of the function. Less attention is paid to how the human operator will use the automation in the new system or how operator tasks will change. As Riley (1995) pointed out, when considering how automation is used rather than designed, one moves away from the normal sphere of influence (and interest) of system designers.

Nevertheless, understanding how automation is used may help developers produce better automation. After all, designers do make presumptions about operator use of automation. The implicit assumption is that automation will reduce operator errors. For example, automated "solutions" have been proposed for many errors that automobile drivers make: automated navigation systems for route-finding errors, collision avoidance systems for braking too late behind a stopped vehicle, and alertness indicators for drowsy drivers. The critical human factors questions regarding how drivers would use such automated systems have not been examined (Hancock & Parasuraman, 1992; Hancock, Parasuraman, & Byrne, 1996).

Several things are wrong with this approach. First, one cannot remove human error from the system simply by removing the human operator. Indeed, one might think of automation as a means of substituting the designer for the operator. To the extent that a system is made less vulnerable to operator error through the introduction of automation, it is made more vulnerable to designer error. As an example of this, consider the functions that depend on the weight-on-wheels sensors on some modern aircraft. The pilot is not able to deploy devices to stop the airplane on the runway after landing unless the system senses that the gear are on the ground; this prevents the pilot from inadvertently deploying the spoilers to defeat lift or operate the thrust reversers while still in the air. These protections are put in place because of a lack of trust in the pilot to not do something unreasonable and potentially catastrophic. If the weight-on-wheels sensor fails, however, the pilot is prevented from deploying these devices precisely when they are needed. This represents an error of the designer, and it has resulted in at least one serious incident (Poset, 1992) and accident (Main Commission Aircraft Accident Investigation, 1994).

Second, certain management practices or corporate policies may prevent human operators from using automation effectively, particularly under emergency conditions. The weight-on-wheels sensor case represents an example of the human operator not being able to use automation because of prior decisions made by the designer of automation. Alternatively, even though automation may be designed to be engaged flexibly, management may not authorize its use in certain conditions. This appears to have been the case in a recent accident involving a local transit train in Gaithersburg, Maryland. The train collided with a standing train in a heavy snowstorm when the automatic speed control system failed to slow the train sufficiently when approaching the station because of snow on the tracks. It was determined that the management decision to refuse the train operator's request to run the train manually because of poor weather was a major factor in the accident (National Transportation Safety Board, 1997a). Thus automation can also act as a surrogate for the manager, just as it can for the system designer.

Third, the technology-centered approach may place the operator in a role for which humans are not well suited. Indiscriminate application of automation, without regard to the resulting roles and responsibilities of the operator, has led to many of the current complaints about automation: for example, that it raises workload when workload is already high and that it is difficult to monitor and manage. In many cases, it has reduced operators to system monitors, a condition that can lead to overreliance, as demonstrated earlier.

Billings (1991) recognized the danger of defining the operator's role as a consequence of the application of automation. His human-centered approach calls for the operator to be given an active role in system operation, regardless of whether automation might be able to perform the function in question better than the operator. This recommendation reflects the idea that the overall system may benefit more by having an operator who is aware of the environmental conditions the system is responding to and the status of the process being performed, by virtue of active involvement in the process, than by having an operator who may not be capable of recognizing problems and intervening effectively, even if it means that system performance may not be as good as it might be under entirely automatic control. Underlying this recognition is the understanding that only human operators can be granted fiduciary responsibility for system safety, so the human operator should be at the heart of the system, with full authority over all its functions.

Fourth, when automation is granted a high level of authority over system functions, the operator requires a proportionately high level of feedback so that he or she can effectively monitor the states, behaviors, and intentions of the automation and intervene if necessary. The more removed the operator is from the process, the more this feedback must compensate for this lack of involvement; it must overcome the operator's complacency and demand attention, and it must overcome the operator's potential lack of awareness once that attention is gained. The importance of feedback has been overlooked in some highly automated systems (Norman, 1990). When feedback has to compensate for the lack of direct operator involvement in the system, it takes on an additional degree of importance.

In general, abuse of automation can lead to problems with costs that can reduce or even nullify the economic or other benefits that automation can provide. Moreover, automation abuse can lead to misuse and disuse of automation by operators. If this results in managers' implementing additional high-level automation, further disuse or misuse by operators may follow, and so on, in a vicious circle.

## CONCLUSIONS: DESIGNING FOR AUTOMATION USAGE

Our survey of the factors associated with the use, misuse, disuse, and abuse of automation points to several practical implications for designing for more effective automation usage. Throughout this paper we have suggested many strategies for designing, training for, and managing automation based on these considerations. These strategies can be summarized as follows.

### *Automation Use*

1. Better operator knowledge of how the automation works results in more appropriate use of automation. Knowledge of the automation design philosophy may also encourage more appropriate use.

2. Although the influences of many factors affecting automation use are known, large individual differences make systematic prediction of automation use by specific operators difficult. For this reason, policies and procedures should highlight the importance of taking specific considerations into account when deciding whether or not to use automation, rather than leaving that decision vulnerable to biases and other factors that may result in suboptimal strategies.

3. Operators should be taught to make rational automation use decisions.

4. Automation should not be difficult or time consuming to turn on or off. Requiring a high level of cognitive overhead in managing automation defeats its potential workload benefits, makes its use less attractive to the operator, and makes it a more likely source of operator error.

### *Automation Misuse*

1. System designers, regulators, and operators should recognize that overreliance happens and should understand its antecedent conditions and consequences. Factors that may lead to overreliance should be countered. For example, workload should not be such that the operator fails to monitor automation effectively. Individual

operators who demonstrate a bias toward overreliance because of specific factors should be taught to recognize these biases and compensate for them. Overreliance on automation may also signal a low level of self-confidence in the operator's own manual control skills, suggesting that further training or evaluation of the operator's suitability for the job is needed.

2. Operators use automation cues as heuristics for making decisions. Although the use of heuristics is usually effective, occasionally it may lead to error because of decision biases. Training is required to recognize and counter decision biases that may lead to overreliance on automation.

3. Although it is often pointed out that human monitoring is subject to errors, in many instances operational monitoring can be efficient. Human monitoring tends to be poor in work environments that do not conform to well-established ergonomics design principles, in high-workload situations, and in systems in which the automation is highly autonomous and there is little opportunity for manual experience with the automated tasks.

4. Feedback about the automation's states, actions, and intentions must be provided, and it must be salient enough to draw operator attention when he or she is complacent and informative enough to enable the operator to intervene effectively.

*Automation Disuse*

1. The impact of automation failures, such as false alarm rates, on subsequent operator reliance on the automation should be considered as part of the process of setting automation performance requirements, otherwise, operators may grow to mistrust the automation and stop using it. When the operator makes an error, system designers and managers may grow to mistrust the operator and look to automation as the ultimate authority in the system.

2. Designers of automated alerting systems must take into account not only the decision threshold at which these systems are set but also the base rate of the hazardous condition to be detected.

3. Designers of automated alerting systems should consider using alarms that indicate when a dangerous situation is possible ("likelihood" alarms), rather than encouraging the operator to rely on the alarm as the final authority on the existence of a dangerous condition.

*Automation Abuse*

1. The operator's role should be defined based on the operator's responsibilities and capabilities, rather than as a by-product of how the automation is implemented.

2. The decision to apply automation to a function should take into account the need for active operator involvement in the process, even if such involvement reduces system performance from what might be achieved with a fully automated solution; keeping the operator involved provides substantial safety benefits by keeping the operator informed and able to intervene.

3. Automation simply replaces the operator with the designer. To the extent that a system is made less vulnerable to operator error through the application of automation, it is made more vulnerable to designer error. The potential for and costs of designer error must be considered when making this trade-off.

4. Automation can also act as a surrogate for the manager. If the designer applied a specific automation philosophy to the design of the system, that philosophy should be provided to the manager so that operational practices are not imposed that are incompatible with the design. In addition, just as system designers must be made aware of automation-related issues, so must those who dictate how it will be used.

Finally, two themes merit special emphasis. First, many of the problems of automation misuse, disuse, and abuse arise from differing expectations among the designers, managers, and operators of automated systems. Our purpose is not to assign blame to designers, managers, or operators but to point out that the complexities of the operational environment and individual human operators may cause automation to be used in ways different from how designers and managers intend. Discovering the root causes of these differences is a necessary step toward informing the expectations of designers and managers so that operators are provided with automation that better meets their needs and are given the authority and decision-making tools required to use the automation to its best effect.

Second, individual differences in automation use are ubiquitous. Human use of automation is complex, subject to a wide range of influences, and capable of exhibiting a wide range of patterns and characteristics. That very complexity makes the study of automation a large undertaking, but the growing importance of automation in systems makes such study increasingly imperative. Better understanding of why automation is used, misused, disused, and abused will help future designers, managers, and operators of systems avoid many of the errors that have plagued those of the past and present. Application of this knowledge can lead to improved systems, the development of effective training curricula, and the formulation of judicious policies and procedures involving automation use.

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