25. Human Factors in Automation Design

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Designers frequently look toward automation as a way to increase system efficiency and safety by reducing human involvement. This approach often leads to disappointment because the role of people becomes more, not less, important as automation becomes more powerfull and prevalent. Developing automation without consideration of the human operator leads to new and more catastrophic failures. For automation to fulfill its promise, designers must avoid a technology-centered approach and adopt an approach that considers the joint operator–automation system. Automation-related problems arise because introducing automation changes the type and extent of feedback that operators receive, as well as the nature and structure of tasks. In addition, operators' behavioral, cognitive, and emotional responses to these changes can leave the system vulnerable to failure. Automation is not a homogenous technology. There are many types of automation and each poses different design challenges. This chapter describes how different types of automation place different demands on operators. It also presents strategies that can help designers achieve the promise of automation. The chapter concludes with future challenges in automation design.

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Designers often view automation as the path toward greater efficiency and safety. In many cases, automation does deliver these benefits. In the case of the control of cargo ships and oil tankers, automation has made it possible to operate a vessel with as few as 8–12 crew members, compared with the 30–40 that were required 40 years ago [25.1]. In the case of aviation, automation has reduced flight times and increased fuel efficiency [25.2]. Similarly, automation in the form of decision-support systems has been credited with saving millions of dollars in guiding policy and production decisions [25.3]. Automation promises greater efficiency, lower workload, and fewer human errors; however, these promises are not always fulfilled.

A common fallacy is that automation can improve system performance by eliminating human variability and errors. This fallacy often leads to mishaps that surprise operators, managers, and designers. 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 only discovered when the ship ran aground [25.4, 5]. As this example shows, automation does not guarantee improved efficiency and error-free performance.

For automation to fulfill its promise, designers must focus not on the design of the automation, but on the design of the joint human–automation system. 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 a new set of tasks [25.6].

One way to view the automation failure that led to the grounding of the Royal Majesty is that it was simply a malfunction of an otherwise well-designed system – a problem with the technical implementation. Another view is that the grounding occurred because the interface design failed to support the new navigation task and failed to counteract a general tendency for people to overrely on generally reliable automation – a problem with human–technology integration. Although it is often easiest to blame automation failures on technical problems or on human errors, many problems result from a failure to consider the challenges of designing not just automation, but a joint human–automation system.

Automation fails because the role of the person performing the task is often underestimated, particularly the need for people to compensate for the unexpected. Although automation can handle typical cases it often lacks the flexibility of humans to handle unanticipated situations. Avoiding these failures requires a design process with a focus on the joint human–automation system. In most applications, neither the human nor the automation can accommodate all situations – each has limits. Successful automation design must empower the operator to compensate for the limits of the automation and help the operator capitalize on the capabilities of the automation.

This chapter provides an overview of some of the problems frequently encountered with automation. It then describes how these problems relate to types of automation and what design strategies can help designers achieve the promise of automation. The chapter concludes with future challenges in automation design.

25.1 Automation Problems

Automation is often designed and implemented with a focus on the technical aspects of sensors, algorithms, and actuators. These are necessary but not sufficient design considerations to ensure that automation enhances system performance. Such a technology-centered approach often confronts the human operator with challenges that lead to system failures. Because automation often dramatically extends the influence of operators on the system (e.g., automation makes it possible for one person to do the work of ten), the consequences of these failures can be catastrophic. The factors underlying these failures are complex and interacting. Failures arise because introducing automation changes the type and extent of feedback that operators receive, as well as the nature and structure of tasks. In addition, operators' behavioral, cognitive, and emotional response to these changes can leave the system vulnerable to failure. A technology-centered approach to automation design often ignores these challenges, and as a consequence, fails to realize the promise of automation.

25.1.1 Problems Due to Changes in Feedback

Feedback is central to control. One reason why automation fails is that automation often dramatically changes the type and extend of the feedback the operator receives. In the context of driving a car, the driver keeps the car in the center of the lane by adjusting the steering wheel according to visual feedback regarding the position of the car on the road and haptic feedback from the forces on the steering wheel. Emerging vehicle technology may automate lane keeping. Such automation may leave the driver with the visual cues, but may remove the haptic cues. Diminished or eliminated feedback is a common occurrence with automation and it can leave people less prepared to intervene if manual control is required [25.7, 8].

Automation can replace the feedback available in manual control with qualitatively different feedback. As an example, introducing automation into paper-making plants moved operators from the plant floor and placed them in control rooms. This move distanced them from the physical process and eliminated the informal feedback associated with vibrations, sounds, and smells that many operators relied upon [25.9]. At best, this change in cues requires operators to relearn how to control the plant. At worst, the instrumentation and associated displays may not have the information needed for operators to diagnose automation failures and intervene appropriately. Automation can also qualitatively shift the feedback from raw system data to processed, integrated information. Although such integrated data can be simple and easily understood, particularly during routine situations, it may also lack the detail necessary to detect and understand system failures. As an example, the bridge of the cruise ship Royal Majesty had an electronic chart that automatically integrated inertial and GPS navigation data to show operators their position relative to their intended path. This high-level representation of the ship's position remained on the intended course even when the underlying GPS data were no longer used and the ship's actual position drifted many miles off the intended route. In this case, the lack of low-level data and of any indication of the integrated data quality left operators without the feedback they needed to diagnose and respond to the failures of the automation.

The diminished feedback that accompanies automation often has a direct influence on a mishap, as illustrated by the case of the Royal Majesty. However, diminished feedback can also act over a longer time period to undermine operators' ability to perform tasks. In situations in which the automation takes on the tasks previously assigned to the operator, the operator's skills may atrophy as they go unexercised [25.10]. 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 skills and diminish operators' ability to generate expectations of correct behavior [25.8]. Such deskilling leaves operators without the skills to accommodate the demands of the job if they need to detect failures and assume manual control. 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 [25.11].

Automation design requires the specification of sensor, algorithm, and actuator characteristics and their interactions. A technology-centered approach might stop there; however, automation that works effectively requires specification of the feedback to the operators. Without careful design, implementing automation can eliminate and change feedback in a way that can undermine the ability of automation to enhance system performance.

25.1.2 Problems Due to Changes in Tasks and Task Structure

One reason for automation is that it can relieve operators of labor-intensive and error-prone tasks. Frequently, however, the situation becomes more complex in that automation does not simply relieve the operator of tasks, it changes the nature of tasks that must be performed. In most instances, this means that automation requires new skills of operators. Often automation eliminates simple physical tasks, and leaves complex cognitive tasks that appear easy. These complex, yet superficially easy, tasks often lead organizations to place less emphasis on training. On ships, training and certification unmatched to the demands of the automation have led to accidents because of the operators' misunderstanding of new radar and collision avoidance systems [25.12]. For example, on the exam used by the US Coast Guard to certify radar operators, 75% of the items assess skills that have been automated and are not required by the new technology [25.13]. The new technology makes it possible to monitor a greater number of ships, thereby enhancing the need for interpretive skills such as understanding the rules of the road that govern maritime navigation and the automation. These are the very skills that are underrepresented on the Coast Guard exam. Though automation may relieve the operator of some tasks, it often leads to new and more complex tasks that require more, not less, training.

Automation can also change the nature and structure of tasks so that easy tasks are made easier and hard tasks harder – a phenomenon referred to as clumsy automation [25.14]. As *Bainbridge* [25.15] notes, designers often leave the operator with the most difficult tasks because the designers found them difficult to automate. Because the easy tasks have been automated, the operator has less experience and an impoverished context for responding to the difficult tasks. 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 (e.g., straight and level flight or a routine climb) easier, but high-workload phases (e.g., 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 many other domains, such as the operating room [25.16, 17].

The effects of clumsy automation often occur at the level of individual operators and over the span of several minutes, but such effects can also occur across teams of operators over hours or days of operation. Such macrolevel clumsy automation is evident in maritime operations, where automation used for open-ocean sailing reduces the task requirements of the crew, prompting reductions in the crew size. In this situation, automation can have the consequence of making the easy part of the voyage (e.g., open-ocean sailing) easier and the hard part (e.g., port activities) harder [25.18]. Avoiding clumsy automation requires a broad consideration of how automation affects the task structure of operators.

Because automation changes the task structure, new forms of human error often emerge. Ironically, managers and system designers introduce automation to eliminate human error, but new and more disastrous errors often result, in part because automation extends the scope of and reduces the redundancy of human actions. As a consequence, human errors may be more likely to go undetected and do more damage; for example, a flight-planning system for pilots can induce dramatically poor decisions because the automation assumes weather forecasts represent reality and lacks the flexibility to consider situations in which the actual weather might deviate from the forecast [25.19].

Automation-induced errors also occur because the task structure changes in a way that undermines collaboration between operators. Effective system performance involves performing both formal and informal tasks. Informal tasks enable operators to compensate for the limits of the formal task structure; for example, with paper charts mariners will check each others' work, share uncertainties, and informally train each other as positions are plotted [25.20]. Eliminating these informal tasks can make it more difficult to detect and recover from errors, such as the one that led to the grounding of the Royal Majesty. Automation can also disrupt the cooperation between operators reflected in these informal tasks. Cooperation occurs when a person acts in a way that is in the best interests of the group even when it is contrary to his or her own best interests. Most complex, multiperson systems depend on cooperation. Automation can disrupt interactions between people and undermine the ability and willingness of one operator to compensate for another. Because automation also acts on behalf of people, it can undermine cooperation by giving one operator the impression that another operator is acting in a competitive manner, even though the automation's behavior may be due to a malfunction [25.21].

Automation does not simply eliminate tasks once performed by the operator. It changes the task structure and creates new tasks that need to be supported, thereby opening the door to new types of error. Contrary to the expectations of a technology-centered approach to automation design, introducing automation makes it more rather than less important to consider the operators' tasks and role.

25.1.3 Problems Due to Operators' Cognitive and Emotional Response to Changes

Automation sometimes causes problems because it changes operators' feedback and tasks. Operators' cognitive and emotional responses to these changes can amplify these problems; for example, as automation changes the operator's task from direct control to monitoring, the operator may be more prone to direct attention away from the monitoring task, further diminishing the feedback the operator receives from the system. The tendency to trust and complacently rely on automation, particularly during multitask situations, may underlie this tendency to disengage from the monitoring task [25.22–24].

People are not passive recipients of the changes to the task structure that automation makes. Instead, people adapt to automation and this adaptation leads to a new task structure. One element of this adaptation is captured by the ideas of reliance and compliance [25.25]. Reliance refers to the degree to which operators depend on the automation to perform a function. Compliance refers to the degree to which automation changes the operators' response to a situation. Inappropriate reliance and compliance are common automation problems that occur when people rely on or comply with automation in situations where it performs poorly, or when people fail to capitalize on its capabilities [25.26].

Maladaptive adaptation generally, and inappropriate reliance specifically, depends, in part, on operators' attitudes, such as trust and self-confidence [25.27, 28]. 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 [25.29]. Several studies have shown that trust is a useful concept in describing human–automation interaction, both in naturalistic [25.9] and in laboratory settings [25.30–33].

These and other studies show that people tend to rely on automation they trust and to reject automation they do not trust [25.29]. 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 [25.34]. People respond socially to technology in a way that is similar to how they respond to other people [25.35]. *Sheridan* had a similar insight, and suggested that, just as trust mediates relationships between people, it may also mediate relationships between people and automation [25.36, 37]. Because trust often has a powerful effect on mediating relationships between people, trust might exert a similarly strong effect on mediating reliance and compliance with automation [25.38–42].

Inappropriate reliance often stems from a failure of trust to match the true capabilities of the automation. Calibration refers to the correspondence between a person's trust in the automation and the automation's capabilities [25.29]. Overtrust is poor calibration in which trust exceeds system capabilities; with distrust, trust falls short of automation capabilities. Trust often responds to automation as one might expect; it increases over time as automation performs well and declines when automation fails. Importantly, however, trust does not always follow the changes in automation performance. Often, it is poorly calibrated. Trust displays inertia and changes gradually over time rather than responding immediately to changes in automation performance. After a period of unreliable performance, trust is often slow to recover, remaining low even when the automation performs well [25.43]. More surprisingly, trust sometimes depends on surface features of the system that seem unrelated to its capabilities, such as the colors and layout of the interface [25.44–46].

Attitudes such as trust and the associated influence on reliance can exacerbate automation problems such as clumsy automation. As noted earlier, clumsy automation occurs when automation makes easy tasks easier and hard tasks harder. Inappropriate trust can make automation more clumsy because it leads operators to be more willing to delegate tasks to the automation during periods of low workload, compared with periods of high workload [25.15]. This observation demonstrates that clumsy automation is not simply a problem of task structure, but one that depends on operator adaptation that is mediated by attitudes, such as trust.

The automation-related problems associated with inappropriate trust often stem from operators' shift from being a direct controller to a monitor of the automation. This shift also changes how operators receive feedback. Automation shifts people from direct involvement in the action–perception loop to supervisory control [25.47, 48]. Passive observation associated with supervisory control is qualitatively different than active monitoring associated with manual control [25.49, 50]. In manual control, perception directly supports control, and control actions guide perception [25.51]. Monitoring automation disconnects the operators' actions from actions on the system. Such disconnects can undermine the operator's mental model (i. e., their working knowledge of system dynamics, structure, and causal relationships between components), leaving the mental model inadequate to guide expectations and control [25.52, 53].

The shift from direct controller to supervisory controller can also have subtle but important effects on behavior as operators adapt to the automation. Over time automation can unexpectedly shift operators' safety norms and behavior relative to safety boundaries. Behavioral adaptation describes this effect and refers to the tendency of operators to adapt to the new capabilities of the automation in which they change their behavior 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 [25.54–56], organizational [25.57], and societal levels [25.58].

Antilock brake systems (ABS) for cars demonstrate behavioral adaptation. ABS automatically modulates brake pressure 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, ABS has not produced the expected safety benefits. One reason is that drivers of cars with ABS tend to drive less conservatively, adopting higher speeds and shorter following distances [25.59]. Vision enhancement systems provide another example of behavioral adaption. These systems make it possible for drivers to see more at night – a potential safety enhancement; however, drivers tend to adapt to the vision systems by increasing their speed [25.60].

A related form of behavioral adaptation that undermines the benefits of automation is the phenomenon in which the presence of the automation causes a diffusion of responsibility and a tendency to exert less effort when the automation is available [25.61,62]. As a result, people tend to commit more omission errors (failing to detect events not detected by the automation) and more commission errors (incorrectly concurring with erroneous detection of events by the automation) when they work with automation. 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 with individually [25.63].

The issues noted above have primarily addressed the direct performance problems associated with automation. Job satisfaction is another human–automation interaction issue that goes well beyond performance to consider the morale and moral implications of the worker whose job is being changed by automation [25.64]. 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 deskilling a job, making skills that operators worked for years to perfect suddenly obsolete. Properly implemented, automation should reskill workers and make it possible for them to leverage their old skills into new ones that are extended by the support of the automation. Many operators are highly skilled and proud of their craft; automation can either empower or demoralize them [25.9]. Demoralized operators may fail to capitalize on the potential of an automated system.

The cognitive and emotional response of operators to automation can also compromise operators' health. If automation creates an environment in which the demands of the work increase, but the decision latitude decreases, it may then lead to problems ranging from increased heart disease to increased incidents of depression [25.65]. However, if automation extends the capability of the operator and gives him or her greater decision latitude, job satisfaction and health can improve. As an example of improved satisfaction, night-shift operators who had greater decision latitude than day-shift operators leveraged their increased latitude to learn how to manage the automation more effectively [25.9].

Automation problems can be described independently, but they often reflect an interacting and dynamic process [25.66]. One problem can lead to another through positive feedback and vicious cycles. As an example, inadequate training may lead the operator to disengage from the monitoring task. This disengagement leads to poorly calibrated trust and overreliance, which in turn leads to skill loss and further disengagement. 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 byproduct is likely to initiate these negative dynamics.

25.2 Characteristics of the System and the Automation

The likelihood and consequences of automation-related problems depend on the characteristics of the automation and the system being controlled. Automation is not a homogenous technology. Instead, there are many types of automation and each poses different design challenges. As an example, automation can highlight, alert, filter, interpret, decide, and act for the operator. It can assume different degrees of control and can operate over timescales that range from milliseconds to months. The type of automation and the operating environment interact with the human to produce the problems just discussed. As an example, if only a single person manages the system then diminished cooperation and collaboration are not a concern. Some important system and automation characteristics include:

- Automation as information processing stages
- Automation authority and autonomy
- Complexity and observability
- Time-scale and multitasking demands
- Agent interdependencies
- Interaction with environment.

25.2.1 Automation as Information Processing Stages

Defining automation in terms of information processing stages describes it according to the information processing functions of the person that it supports or replaces. Automation can sense the world, analyze information, identify appropriate responses to states of the world or control actuators to change those states [25.67]. Information acquisition automation refers to technology that replaces the process of human perception. Such automation highlights targets [25.68, 69], provides alerts and warnings [25.70, 71], organizes, prioritizes, and filters information. Information analysis automation refers to technology that supplants the interpretation of a situation. An example of this type of automation is a system that critiques a diagnosis generated by the operator [25.72]. Action selection automation refers to technology that combines information in order to make decisions on behalf of 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 [25.73]. Action implementation automation supplants the operators' activity in executing a response. The types of automation at each of these four stages of information process can differ according to degree of authority and autonomy.

Automation authority and autonomy concern the degree to which the automation can influence the system [25.74]. Authority reflects the extent to which the automation amplifies the influence of operators' actions and overrides the actions of other agents. One facet of authority concerns whether or not operators interact with automation by switching between manual and automatic control. With some automation, such as cruise control in cars, drivers simply engage or disengage the automation, whereas automation on the flight deck involves managing a complex network of modes that are appropriate for some situations and not for others. Interacting with such flight-deck automation requires the operator to coordinate multiple goals and strategies to select the mode of operation that fits the situation [25.75]. With such multilevel automation the idea of manual control may not be relevant, and so the issues of skill loss and other challenges with manual intervention may be of less concern. The problems with high-authority, multilevel automation are more likely to be those associated with mode confusion and configuration errors.

Autonomy reflects the degree to which automation acts without operator knowledge or opportunity to intervene. *Billings* [25.11] describes two levels of autonomy: *management by consent*, in which the automation acts only with the consent of the operator, and *management by exception*, in which automation initiates activities autonomously. As another example, automation can either highlight targets [25.68, 69], filter information, or provide alerts and warnings [25.70, 71]. Highlighting targets exemplifies a relatively low degree of autonomy 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 higher degree of autonomy because operators are forced to attend to the information the automation deems relevant. Alerts and warnings similarly exemplify a relatively high level of autonomy because they guide the operator's attention to automation-dictated information and environmental states. High levels of authority and autonomy make automation appear to act as an independent agent, even if the designers had not intended operators to perceive it as such [25.76]. High levels of these two automation characteristics are an important cause of clumsy automation and mode error and can also undermine cooperation between people [25.77].

25.2.2 Complexity and Observability

Complexity and observability refer to the degrees of freedom of the automation algorithms and how directly that complexity is revealed to the operator [25.74]. As automation becomes increasingly complex it can transition from what operators might consider a tool that they use to act on the environment to an agent that acts as a semiautonomous partner. According to the agent metaphor, the operator no longer acts directly on the environment, but acts through an intermediary agent [25.78] or intelligent associate [25.79]. As an agent, automation initiates actions that are not in direct response to operators' commands. Automation that acts as an agent is typically very complex and may or may not be observable. One of the greatest challenges with automated agents is that of mutual intelligibility. Instructing the agent to perform even simple tasks can be onerous, and agents that try to infer operators' intent and act autonomously can surprise operators who might lack accurate mental models of agent behavior. One approach is for the agents to learn and adapt to the characteristics of the operator through a process of remembering what they have been being told to do in similar situations [25.80]. After the agent completes a task it can be equally challenging to make the results observable and meaningful to the operator [25.78]. 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 becomes critical [25.75, 81]. The challenges associated with agents reflect a general tradeoff with automation design: more complex automation is often more capable, but less understandable. As a consequence, even though more complex automation may appear superior, the performance of resulting human–automation system may be inferior to that of a simpler, less capable version of the automation.

25.2.3 Time-Scale and Multitasking Demands

This distinction concerns the tempo of the interactions with the automation. The timescale 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. These distinctions can be described in terms of strategic, tactical, and operational automation. Strategic automation concerns balancing values and costs, as well as defining goals; tactical automation, on the other hand, involves setting priorities and coordinating tasks. In contrast, operational automation concerns the moment-to-moment perception of system state and adjustment. With operational automation, operators can experience substantial time pressure as the tempo of activity, on the order of milliseconds to seconds, exceeds their capacity to monitor the automation and still respond in a timely manner to its limits [25.82, 83].

25.2.4 Agent Interdependencies

Agent interdependencies describe how tightly coupled the work of one operator or element of automation is with another [25.6, 57]. In some situations, automation might directly support work of a team of people and in other situations automation might support the activity of a person that has little interaction with others. An important source of automation-related problems is the assumption that automation affects only one person or one set of tasks, causing important interactions with other operators to be neglected. Often seemingly independent tasks may actually be coupled, and automation has a tendency to tighten this coupling. As an example, on the surface, adaptive cruise control affects only the individual driver who is using the system. Because adaptive cruise control responds to the behavior of the vehicle ahead, however, its behavior cannot be considered without taking into account the surrounding traffic dynamics. Failing to consider these interactions of intervehicle velocity changes can lead to oscillations and instabilities in the traffic speed, potentially compromising driver safety [25.84, 85]. Similar failures occur in supply chains, as well as in petrochemical processes where people and automation sometimes fail to coordinate their activities [25.86]. Designing for such situations requires a change in perspective from one centered on a single operator and a single element of automation to one that considers multi-operator–multi-automation interactions [25.87, 88].

25.2.5 Environment Interactions

Interaction with the environment refers to the degree to which the automation system is isolated from or interactive with the surrounding environment. The environmental context can affect the reliability and behavior of the automation, the operator's perception of the automation, and thus the overall effectiveness of the human–automation partnership [25.89–92]. An explicit environmental representation is necessary to understand the joint human–automation performance [25.89].

25.3 Application Examples and Approaches to Automation Design

The previous section described some important characteristics of automation and systems that contribute to automation-related problems. These distinctions help identify design approaches to minimize these problems. This section describes specific strategies for designing effective automation, which include:

- Function allocation with Fitts' list
- Operator–automation simulation and analysis
- Representation aiding and enhanced feedback
- Expectation matching and automation simplification.

25.3.1 Fitts' List and Function Allocation

Function allocation with the Fitt's list is a long-standing technique for identifying the role of operators and automation. This approach assesses each function and whether a person or automation might be best suited to performing it [25.93, 94]. Functions better performed by automation are automated and the operator remains responsible for the rest, and for compensating for the limits of the automation. The relative capability of the automation and human depend on the stage of automation [25.95].

Applying a Fitts' list to determine an appropriate allocation of function has, however, substantial weaknesses. One weakness is that any description of functions is a somewhat arbitrary decomposition of activities that can mask 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 an incoherent collection of functions that were too difficult to automate [25.15]. Another weakness is that this approach neglects the tendency for operators to use automation in unanticipated ways because automation often makes new functions possible [25.96]. Another challenge with this general approach is that it often carries the implicit assumption that automation can substitute for functions previously performed by operators and that operators do not need to be supported in performing functions allocated to the automation [25.97]. This substitution-based function allocation fails to consider the qualitative change automation can bring to the operators' work, and the adaptive nature of the operator.

As a consequence of these challenges, the Fitts' list provides only general guidance for automation design and has been widely recognized as problematic [25.73, 95, 97]. 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 [25.98].

Although imperfect, the Fitts' list approach has some general considerations that can improve design. People tend to be effective in perceiving patterns and relationships amongst data and less so with tasks requiring precise repetition [25.64]. Human memory tends to organize large amounts of related information in a network of associations that can support effective judgments. 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 [25.64].

25.3.2 Operator–Automation Simulation

Operator–automation simulation refers to computer-based techniques that explore the space of operator–automation interaction to identify potential problems. Discrete event simulation tools commonly used to evaluate manufacturing processes are well-suited to operator–automation analysis. Such techniques provide a rough estimate of some of the consequences of introducing automation into complex dynamic systems. As an example, simulation of a supervisory control situation made it possible to assess how characteristics of the automation interacted with the operating environment to govern system performance [25.99]. This analysis showed that the time taken to engage the automation interacted with the dynamics of the environment to undermine the value of the automation such that manual control was more appropriate than engaging the automation.

Although discrete event simulation tools can incorporate cognitive mechanisms and performance constraints, developing this capacity requires substantial effort. For automation analysis that requires a detailed cognitive representation, cognitive architectures, such as adaptive control of thought-rational (ACT-R), offer a promising approach [25.100]. ACT-R is a useful tool for approximating the costs and benefits of various automation alternatives when a simple discrete event simulation does not provide a sufficiently detailed representation of the operator [25.101].

Simulation tools can be used to explore the potential behavior of the joint human–automation system, but may not be the most efficient way of identifying potential human–automation mismatches associated with inadequate mental models and automation-related errors. Network analysis techniques offer an alternative. State-transition networks can describe operator–automation behavior in terms of a finite number of states, transitions between those states, and actions. Figure 25.1 provides an example presentation, defining at a high level the behavior of adaptive cruise control (ACC). This formal modeling language makes it possible to identify automation problems that occur when the interface or the operator's mental model is inadequate to manage the automation [25.102]. Figure 25.2 shows how combining the concurrent processes of the ACC model with its internal states and transitions with the associated driver model of the ACC's behavior reveals

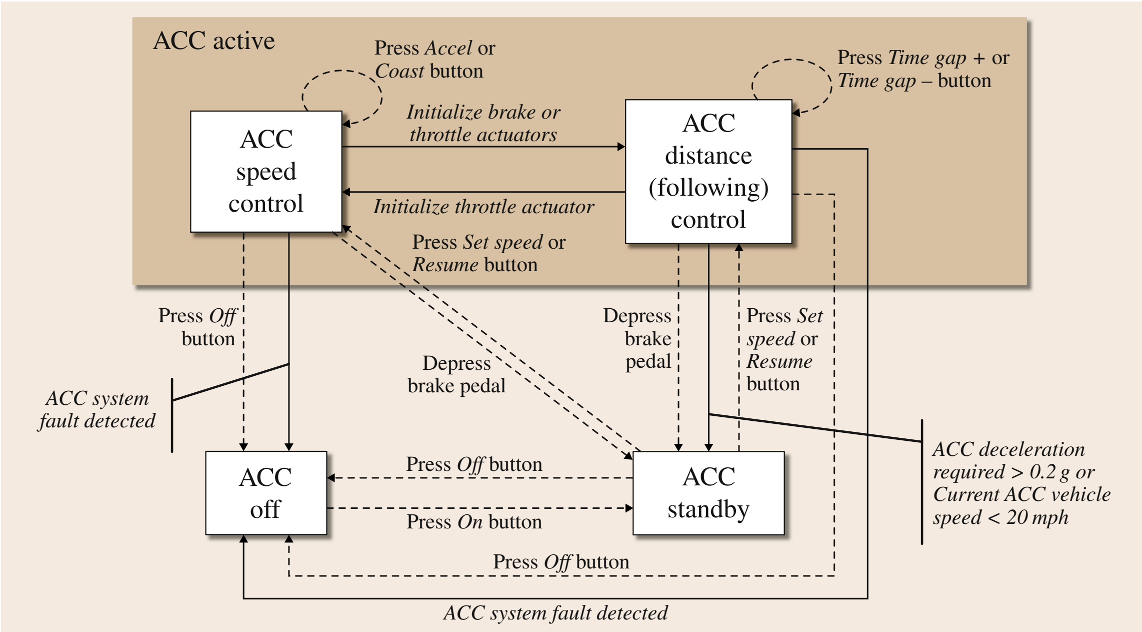

Fig. 25.1 ACC states and transitions. *Dashed lines* represent driver-triggered transitions. *Solid lines* represent ACC-triggered transitions

mismatches. These mismatches can cause automation-related errors and surprises to occur. More specifically, when the automation model enters a particular state and the operator's model does not include this state then the analysis predicts that the associated ambiguity will surprise operators and lead to errors [25.103]. Such ambiguities have been discovered in actual aircraft autopilot systems, and network analysis can identify how to avoid them with improvements to the interface and training materials [25.103].

25.3.3 Enhanced Feedback and Representation Aiding

Enhanced feedback and representation aiding can help prevent problems associated with inadequate feedback that range from developing appropriate trust and clumsy automation to the out-of-the-loop phenomenon. Automation typically lacks adequate feedback [25.104]. 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 [25.105].

A promising approach to avoid overloading the operator is to provide feedback through sensory channels that are not otherwise used (e.g., haptic, tactile, and auditory) to prevent overload of the more commonly used visual channel. Haptic feedback (i. e., vibration on the wrist) has proven more effective in alerting pilots to mode changes of cockpit automation than visual cues [25.106]. Pilots receiving visual alerts only detected 83% of the mode changes, but those with haptic warnings detected 100% of the changes. Importantly, the haptic warnings did not interfere with performance of concurrent visual tasks. Even within the visual modality, presenting feedback in the periphery helped pilots detect uncommanded mode transitions and such feedback did not interfere with concurrent visual tasks any more than currently available automation feedback [25.107]. Similarly, *Seppelt* and *Lee* [25.108] combined a more complex array of variables in a peripheral visual display for ACC. Figure 25.3 shows how this display includes relevant variables for headway control (i. e., time headway, time-to-collision, and range rate) relative to the operating limits of the ACC. This display promoted faster failure detection and more appropriate engagement strategies compared with the standard ACC interface. Although promising, haptic, auditory and peripheral visual displays cannot convey the detail possible in visual displays, making it difficult to convey the complex relationships that some-

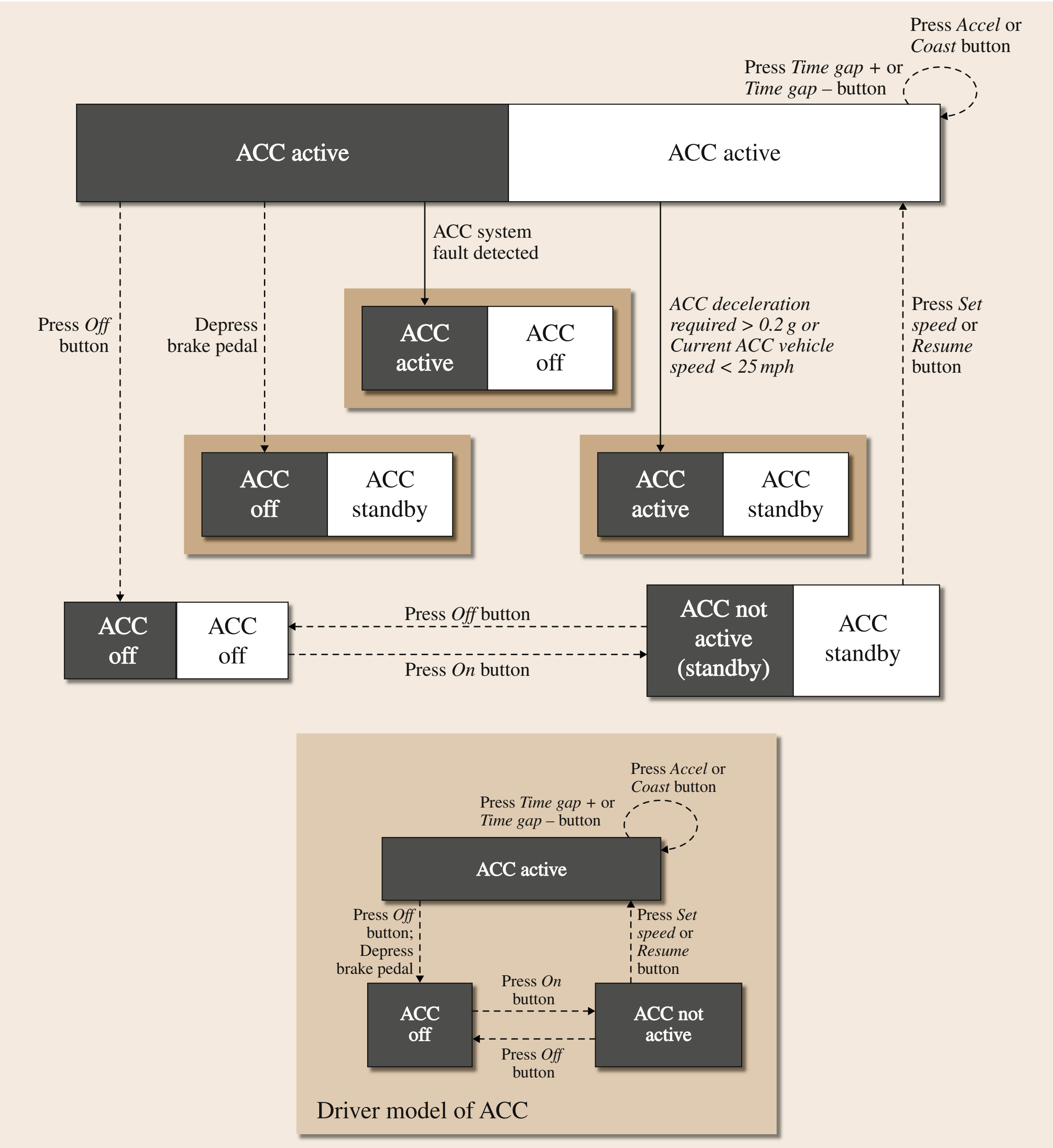

Fig. 25.2 Composite of the driver and ACC models in which corresponding driver model states (*black boxes*) and ACC model states (*white boxes*) are combined into state pairs. Error states, or model mismatches, occur when a particular transition leads to discrepant states. Composite states *ACC not active* (*standby*)/*ACC off*, *ACC off*/*ACC standby*, and *ACC active*/*ACC standby* are error states. The driver is unaware of the shift of the ACC system into standby when deceleration and vehicle speed limits are reached, and of the ACC system disengaging when system faults are detected, as neither state change is clearly communicated to the driver. The state change that results from the driver depressing the brake pedal is similarly ambiguous

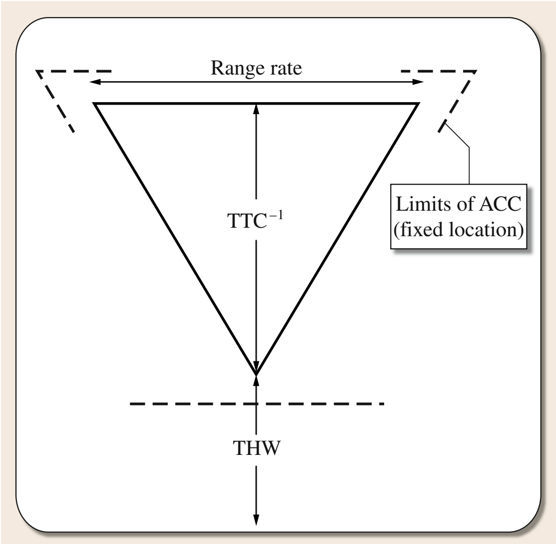

Fig. 25.3 A peripheral display to help drivers understand adaptive cruise control [25.108] (TTC – time-to-collision; THW – time headway

times govern automation behavior. An important design tradeoff emerges: provide sufficient detail regarding automation behavior, but avoid overloading and distracting the operator.

Simply enhancing the feedback operators receive regarding the automation is sometimes insufficient. Without the proper context, abstraction, and integration, feedback may not be understandable. Representation aiding capitalizes on the power of visual perception to convey this complex information; 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 additional effort [25.87]. Using a display that combines pitch, roll, altitude, airspeed, and heading can directly specify task-relevant information such as what is *too low* [25.109] as opposed to operators being required to infer such relationships from the set of variables. Integrating automation-related information with traditional displays and combining low-level data into meaningful information can help operators understand automation behavior.

In the context of process control, *Guerlain* and colleagues [25.110] 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* that 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, which are ambiguous cues as to an increase or decrease in amount. Third, place data in a meaningful context. The meaningful context for any variable depends on what comparisons need to be made. For automation, this includes the allowable ranges relative to the current control variable setting, and the output relative to its desired level. Similarly, *Dekker* and *Woods* [25.97] suggest event-based representations that highlight changes, historical representations that help operators project future states, and pattern-based representations that allow operators to synthesize complex relationships perceptually rather than through arduous mental transformations.

Representation aiding helps operators trust automation appropriately. However, trust also depends on more subtle elements of the interface [25.29]. In many cases, trust and credibility depend on surface features of the interface that have no obvious link to the true capabilities of the automation [25.111, 112]. An online survey of over 1400 people found that for web sites, credibility depends heavily on *real-world feel*, which is defined by factors such as response speed, a physical address, and photos of the organization [25.113]. Similarly, a formal photograph of the author enhanced trustworthiness of a research article, whereas an informal photograph decreased trust [25.114]. 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.

25.3.4 Expectation Matching and Simplification

Expectation matching and simplification help operators understand automation by using algorithms that are more comprehensible. One strategy is to simplify the automation by reducing the number of functions, modes, and contingencies [25.115]. Another is to match its algorithms to the operators' mental model [25.116]. Automation designed to perform in a manner consistent with operators' mental model, preferences, and expectations can make it easier for operators to recognize failures and intervene. Expectation matching and simplification are particularly effective when a technology-centered approach has created an overly complex array of modes and features.

ACC is a specific example of where matching the mental model of an operator to the automation's algorithms may be quite effective. Because ACC can only apply 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 can make the difference in avoiding a collision. If the automation behaves in a manner consistent with drivers' expectations, drivers will be more likely to detect and respond to the operational limits of the automation quickly [25.116]. *Goodrich* and *Boer* [25.116] designed an ACC algorithm consistent with drivers' mental models such that ACC behavior was partitioned according to perceptually relevant variables of inverse time-to-collision and time headway. Inverse time-to-collision is the relative velocity divided by the distance between the vehicles. Time headway is the distance between the vehicles divided by the velocity of the driver's vehicle. Using these variables it is possible to identify a perceptually salient boundary that separates routine speed regulation and headway maintenance from active braking associated with collision avoidance.

For situations in which the metaphor for automation is an agent, the mental model people may adopt to understand the automation is that of a human collaborator. Specifically, *Miller* [25.117] 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. Some examples of automation etiquette are for the automation to make it easy for operators to override and recover from errors, to enable interaction features only when and if necessary, to explain what is being done and why, to interrupt operators only in emergency situations, and to provide information that is unique to the information known by the operator.

Developing automation etiquette could promote appropriate trust, but also has the potential to 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 [25.35, 118]. 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 lead to many different mental models and expectations. 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 [25.119]. Mental models often contain misconceptions, and transferring these to the automation could lead to serious misunderstandings and automation failures. Even if an operator's mental model is consistent with the system constraints, automation based on such a mental model may not achieve the same benefits as automation based on more sophisticated algorithms. In this case, designers must consider the tradeoff between the benefits of a complex control algorithm and the costs of an operator not understanding that algorithm. Enhanced feedback and representation aiding can mitigate this tradeoff.

25.4 Future Challenges in Automation Design

The previous section outlined strategies that can make the operator–automation partnership more effective. As illustrated by the challenges in applying the Fitts' list, the application of these strategies, either individually or collectively, does not guarantee effective automation. In fact, the rapid advances in software and hardware development, combined with an ever expanding range of applications, make future problems with automation likely. The following sections highlight some of these emerging challenges. The first concerns the demands of managing swarm automation, in which many semiautonomous agents work together. The second concerns large, interconnected networks of people and automation, in which issues of cooperation and competition become critical. These examples represent some emerging challenges facing automation design.

25.4.1 Swarm Automation

Swarm automation consists of many simple, semiautonomous entities whose emergent behavior provides a robust response to environmental variability. Swarm automation has important applications in a wide range of domains, including planetary exploration, unmanned aerial vehicle reconnaissance, land-mine neutralization, and intelligence gathering; in short, it is applicable in any situation in which hundreds of simple agents might be more effective than a single, complex agent. Biology-inspired robotics provides 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 [25.120, 121]. The swarm robot concept assumes that small robots with simple behaviors can perform important functions more reliably and with lower power and mass requirements than can larger robots [25.122–124]. Typically, the simple algorithms controlling the individual entity can elicit desirable emergent behaviors in the swarm [25.125, 126]. As an example, the collective foraging behavior of honeybees shows that agents can act as a coordinated group to locate and exploit resources without a complex central controller.

In addition to physical examples of swarm automation, swarm automation has potential in searching large complex data sets for useful information. Current approaches to searching such data sources are limited. People miss important documents, disregard data that is a significant departure from initial assumptions, misinterpret data that conflicts with an emerging understanding, and disregard more recent data that could revise interpretation [25.127]. The parameters that govern discovery and exploitation of food sources for ants might also apply to the control of software agents in their discovery and exploitation of information. Just as swarm automation might help explore physical spaces, it might also help explore information spaces [25.128].

The concept of hortatory control describes some of the challenges of controlling swarm automation. Hortatory control describes situations where the system being controlled retains a high degree of autonomy and operators must exert indirect rather than direct control [25.129]. Interacting with swarm automation requires people to consider swarm dynamics and not just the behavior of the individual agents. In these situations, it is most useful for the operator to control parameters affecting group rather than individual agents and to receive feedback about group rather than individual behavior. Parameters for control might include the degree to which each agent tends to follow successful agents (positive feedback), the degree to which they follow the emergent structure of their own behavior (stigmergy), and the amount of random variation that guides their paths [25.130]. In exploration, a greater amount of random variation will lead to a more complete search, and a greater tendency to follow successful agents will speed search and exploitation [25.131]. Swarm automation has great potential to extend human capabilities, but only if a thorough empirical and analytic investigation identifies the display requirements, viable control mechanisms, and the range of swarm dynamics that can be comprehended and controlled by humans [25.132].

25.4.2 Operator–Automation Networks

Complex operator–automation networks emerge as automation becomes more pervasive. In this situation, the appropriate unit of analysis shifts 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. The factors affecting microlevel behavior may have unexpected effects on macrolevel behavior [25.133]. As the degree of coupling increases, poor coordination between operators and inappropriate reliance on automation has greater consequences for system performance [25.6].

Supply chains represent an increasingly important example of multi-operator–multi-automation systems. 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. 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. Increasingly, manufacturers rely on supply chains [25.134] and attempt to manage them with automation [25.86].

Supply chains suffer from serious problems that erode their promised benefits. One is the bullwhip effect, in which small variations in end-item demand induces large-order oscillations, excess inventory, and back-orders [25.135]. The bullwhip effect can undermine a company's efficiency and value. Automation that forecasts demands can moderate these oscillations [25.136, 137]. However, people must trust and rely on that automation, and substantial cooperation between supply-chain members must exist to share such information.

Vicious cycles also undermine supply-chain performance, through an escalating series of conflicts between members [25.138]. Vicious cycles can have dramatic negative consequences for supply chains; for example, a strategic alliance between Office Max and Ryder International Logistics devolved into a legal fight in which Office Max sued Ryder for US $21.4 million and then Ryder sued Office Max for US $75 million [25.139]. Beyond the legal costs, these breakdowns threaten competitiveness and undermine the market value of the companies involved [25.134]. 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 of diminishing cooperation.

Inappropriate use of automation can contribute to both vicious cycles and the bullwhip effect, but has received little attention. A recent study used a simulation model to examine how reliance on automation influences cooperation and how sharing two types of automation-related information influences cooperation between operators in the context of a two-manufacturer one-retailer supply chain [25.21]. This study used a decision field-theoretic model of the human operator [25.140, 141] to assess the effects of automation failures on cooperation and the benefit of sharing automation-related information in promoting cooperation. Sharing information regarding automation performance improved operators' reliance on automation, and the more appropriate reliance promoted cooperation by avoiding unintended competitive behaviors caused by inappropriate use of automation. Sharing information regarding the reliance on automation increased willingness to cooperate even when the other occasionally engaged in competitive behavior. Sharing information regarding the operators' reliance on automation led to a more charitable interpretation of the other's intent and therefore increased trust in the other operator. The consequence of enhanced trust is an increased chance of cooperation. Figure 25.4 shows that these two types of information sharing influence cooperation and result in an additive improvement in cooperation. This preliminary simulation study showed that cooperation depends on the appropriate use of automation and that sharing automation-related information can have a profound effect on cooperation, a result that merits verification with experiments with human subjects.

The interaction between automation, cooperation, and performance seen with supply-chain management may also apply to other domains; for example, power-grid management involves a decentralized network that makes it possible to efficiently supply the USA with power, but it can fail catastrophically when cooperation and information-sharing breaks down [25.142]. Similarly, datalink-enabled air-traffic control makes it possible for pilots to negotiate flight paths efficiently, but it can fail when pilots do not cooperate or have trouble anticipating the complex dynamics of the system [25.143, 144]. Overall, technology is creating many highly interconnected networks that have great potential, but also raise important concerns. Resolving these concerns partially depends on designing effective multi-operator–multi-automation interactions.

Swarm automation and complex operator–automation networks pose challenges beyond those of traditional systems and require new design strategies. The automation design strategies described earlier, such as function allocation, operator–automation simulation, representation aiding, and expectation matching are somewhat limited in addressing the new challenges of swarm automation and complex operator–automation networks. A particular challenge in automation design is developing analytic tools, interface designs, and interaction concepts that consider issues of cooperation and coordination in operator–automation interactions. For further discussion on the automation interactions and interface design refer to Chap. 34.

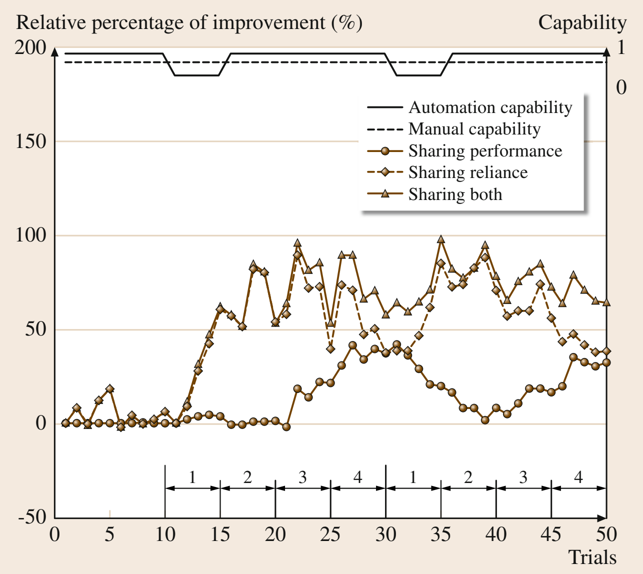

Fig. 25.4 The effect of sharing information regarding the performance of the automation and reliance on the automation [25.21]

Part C | 25.4

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