Factors Affecting Performance of Human-Automation Teams

Anthony L. Baker and Joseph R. Keebler

Abstract Automated systems continue to increase in both complexity and capacity. As such, there is an increasing need to understand the factors that affect the performance of human-automation (H-A) teams. This high-level review examines several such factors: we discuss levels and degrees of automation, the reliability of the automated system, human trust of automation, and workload transitions in the H-A system due to off-nominal events. The influence that each of these factors has on the H-A team dynamic must be more completely understood in order to ensure that the team can perform to its maximum potential. Thorough understanding of this dynamic is especially important to ensuring that H-A teams can succeed safely and effectively in critical contexts.

Keywords Automation · Human-systems integration · Human-Automation teams · Team performance · Reliability · Trust of automation · Off-nominal events

1 Introduction

Since the dawn of the industrial revolution, automation has held the promise of vastly improving the work efficiency of humankind. Within the last few decades, we have seen the human-automation (H-A) relationship change, moving the role of automation from tool to teammate in order to drive and sustain this change. The proliferation of automation has come with the task of understanding how automation fits into the existing puzzle of human working relationships, and there has been much research to guide the process of placing that puzzle piece. This review discusses some of that research.

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P. Savage-Knepshield and J. Chen (eds.), *Advances in Human Factors in Robots and Unmanned Systems*, Advances in Intelligent Systems and Computing 499,
DOI 10.1007/978-3-319-41959-6_27

To put this research into an appropriate context, we will consider the environment that can perhaps place the most demand on an H-A team: the void of space. Considered an ICE—isolated, confined, and extreme—environment, space and future travel through it will require a shift in the way we think about H-A teams. The next frontier in human space exploration is a mission to Mars. With current technology, it would take a human crew about six months to get there, and then six months to return. A mission to land crew on Mars may have to last for several months at the minimum, perhaps more, depending on when the orbits of Earth and Mars provide for favorable launch windows. This long-duration spaceflight (LDSF) means that mission parameters for the human operators will be different from previous missions. The long communication time between mission control on Earth and the astronauts (radio signals can take up to 20–30 min to travel between the planets) means that astronauts will be expected to perform within "bounded autonomy", meaning that they are free to perform most functions as they see fit, with lightly-interspersed input from mission control at critical junctures [1]. Any LDSF mission must consider all of these extra constraints when designing the H-A system, in order to achieve safe, effective, efficient performance.

To this extent, this paper will review several factors that affect the performance of H-A systems. Levels and degrees of automation will be reviewed and considered and the performance impact of reliability of automated systems will be assessed. The human side of the H-A team will be considered, with specific emphasis on factors guiding human trust of automation. We will also consider the consequences of failures in the H-A system, and we will investigate factors that improve performance outcomes after failures. Finally, we will draw conclusions about ways to improve the overall performance of H-A teams, and we will provide directions for future research.

2 Stages and Levels of Automation

Automation is defined by the manner in which it carries out its tasks, and by the extent to which it is given certain types of tasks. Before going further, it would be best to define what we mean by automation, because the term can be used many different ways. We will use "automation" to refer to a computerized or mechanical system used to carry out a role or a type of work performed by humans.

Automated systems can be differentiated in a few ways. There are generally two schools of thought when it comes to describing levels of automation. The first school of thought arose several decades ago with a seminal paper by Sheridan and Verplank [2], which discussed the teleoperation of submersible vehicles and work platforms. The article further discusses control hardware (such as sensors, communication, controls, and the workstation) and how it affects performance of the human operator. This was one of the earlier works which assessed the performance of H-A teams. In order to characterize the automated assets used by the operators, the authors outlined a model to describe different levels of automation that were possible, with each level of automation providing a different level of support to the human's operation of the system. The model is provided in Table 1.

Our original definition of automation referred to the complete or partial replacement of human operation of a task with an automated system. In contrast, the model in Table 1 implies that automation is not all-or-none, but rather that there are distinct levels with various amounts of automation. As the level of automation increases, the amount of work entrusted to the human operator is reduced, as task demands are increasingly offloaded to the automated system. At the 10th level, an automated system is in full control of all decisions and does not inform human operators. Rarely are systems automated to this extent; generally, some level of input from a human, or some ability to inform human operators of task outcomes, is always useful to have.

The second school of thought in defining automation is more recent, and coincides with the rise of information-processing research. Notably, Parasuraman et al. [3] created a model of automation that grounds automation levels in an information-processing paradigm. It is helpful to first consider a simplified model of an information-processing task. An example is provided in Fig. 1.

In the first stage of the model, acquisition, information about the environment and the state of the system is gathered and synthesized from multiple sources. In a human operator, this is done via the senses, while an automated entity will make

Table 1 10 levels of automation, from Sheridan and Verplank [2]

Automation level	Automation description
1	The computer offers no assistance; human must take all decision and actions
2	The computer offers a complete set of decision/action alternatives, or
3	Narrows the selection down to a few, or
4	Suggests one alternative, and
5	Executes that suggestion if the human approves, or
6	Allows the human a restricted time to veto before automatic execution, or
7	Executes automatically, then necessarily informs humans, and
8	Informs the human only if asked, or
9	Informs the human only if it, the computer, decides to
10	The computer decides everything and acts autonomously, ignoring the human

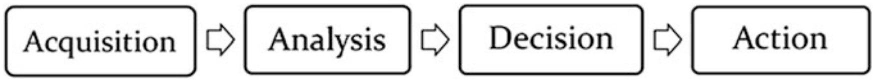

Fig. 1 Information-processing model. While this is a gross simplification of the complexity of human (or machine) information processing, it is useful in understanding the process of going from data acquisition to action execution

use of sensors. This stage includes the allocation of attention and cognitive pre-processing of information. The second stage of the model, analysis, involves working memory to a large extent. Here, the human or automated system will consciously perceive, manipulate, and process retrieved information. In the third stage, cognitive processing is used to derive an appropriate response about the information gathered. In the fourth stage, the decision is acted upon.

What Parasuraman, Sheridan, and Wickens did was to take this four-stage model and describe how each of the stages could have its own levels of automation. This stands in contrast to Sheridan and Verplank's model, which only considers how the automated systems come to their decisions. In this newer model, the entire information-processing process is considered, and each stage can be automated at a different level. This accounts for a multitude of modern computerized systems that are specialized for acquiring and analyzing massive amounts of information very quickly, as well as synthesizing it into a set of choices to be made for a human operator to decide on. As one example, the proliferation of internet-usage data allows companies to collect large amounts of data about how their customers use their sites. Systems are able to harness this information, analyze traffic and purchase patterns, and provide information about what parts of the site are making money, so that the operators can decide on how to capitalize on this information.

Returning to our LDSF context, let us imagine the existence of an automated system which can control power allocation to various systems of a hypothetical spaceship. To what extent should the system be automated? In other words, should all power allocation actions be made as the system deems appropriate? Should actions only be taken when there is a near-perfect chance that the power allocation will not result in failure? What if those conditions are not always met, and the automated system is not able to do much in the way of allocating power, despite its tasking?

The question of the extent of automation is a difficult one. The best solution (and, unfortunately, the one that provides the least amount of guidance at face value) is that a system needs to be automated "just the right amount". If the automated system is only capable of very little, or is only entrusted with menial tasks, human operators are not likely to trust the automated system [4]. However, if the automated system has a very large amount of responsibility, there is potential of a significant "lumberjack effect" [5]. The system is like a large tree in a forest: the bigger it is, the harder it will fall, or in automation terms, the more responsibility the automation has, the greater the performance decrement when the system fails. Onnasch et al. [5] evidence for the existence of a point, called *a*, at which automation should not be given further responsibility, as crossing this point results in significantly worse post-failure performance. The authors provide a chart, reproduced in Fig. 2, which shows the relationships between human operator situational awareness, operator workload, system failure performance, and system routine performance, each as a factor of degree of automation.

Being cognizant of *a* is not enough. System designers for LDSF are given the difficult task of getting as close to *a* as possible without unduly jeopardizing the performance of the human-automation team when a failure in the automated system

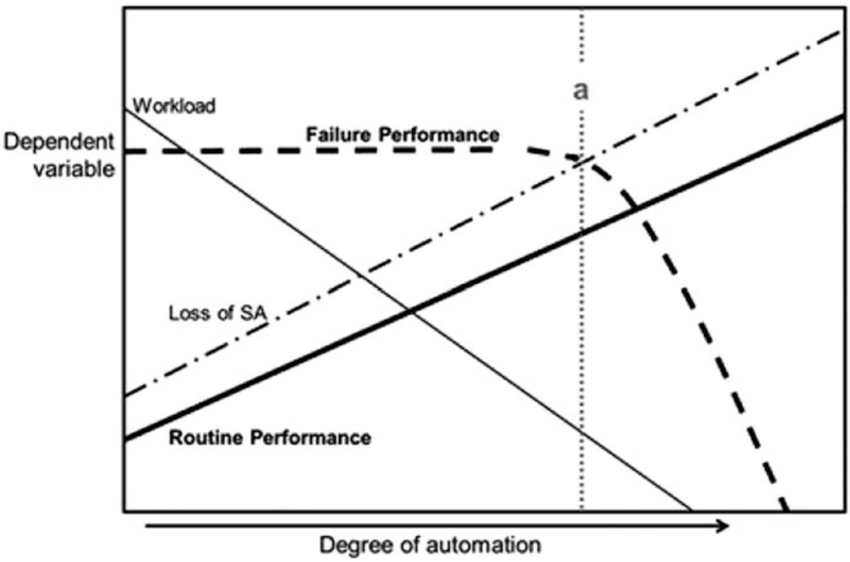

Fig. 2 Several variables as a factor of degree of automation [5]. Note the sharp drop in failure performance after the system is automated past *a*

occurs. The system performance benefits and reductions in operator workload are non-negligible and are the drivers that demand that the degree of automation used is as extensive as is safely possible.

3 Reliability of Automated Systems

Reliability of the automated system is a factor that plays a large role in how the human operator actually uses the system, and in turn, how the system is able to perform. In essence, reliability is the rate at which an automated system performs properly and predictably. Understandably, greater automation leads to greater performance by an H-A team. However, an unreliable automated system places greater task demands on the human operator, who must then compensate for potentially incorrect information, analyses, decisions, or executions of action. Yeh and Wickens [6] assessed the performance of participants on a target-detection task using a cue-detection system that changed in its reliability. Starting off as reliable, the system became unreliable at a certain point in the task. The authors found that participants adjusted their usage of the system to compensate for perceived flaws in the system, with users relying more on their own judgments than those of the system when they believed that the system was unreliable.

User adjustments are not the only outcome of an unreliable system. Rovira et al. [7] conducted a study assessing participants' response times in which they were tasked with deciding whether targets were enemy or friendly. Participants had the support of an automated system, which aided their identification of the targets. This system became similarly unreliable at certain points. The authors found that participant response times were slower when dealing with the unreliable level of automated support, which provides more evidence for the idea that an automated system that is not consistently reliable induces a performance decrement on the human-automation system.

4 Trust of Automation

Predictability of the automated system's choices, actions, and capabilities is important to the human side of the team: as the human's understanding of the automated asset's purpose and abilities increases, the potential performance of the team increases as well [8]. This is referred to as having a shared mental model of the task at hand, in that the user's mental model of the task and the automation fits with the model of what the automation perceives and is capable of. Lee and See [9], who reviewed the existing literature on human trust of automated systems, further inform this congruence between automation capability (i.e. trustworthiness) and operator understanding of the automation. The authors illustrated several concepts that are not new to the field, but which are very useful in understanding the complex relationship of the H-A team (Fig. 3).

User trust of an automated system is considered calibrated when it matches the system's capabilities, and calibrated trust is conducive to effective performance of

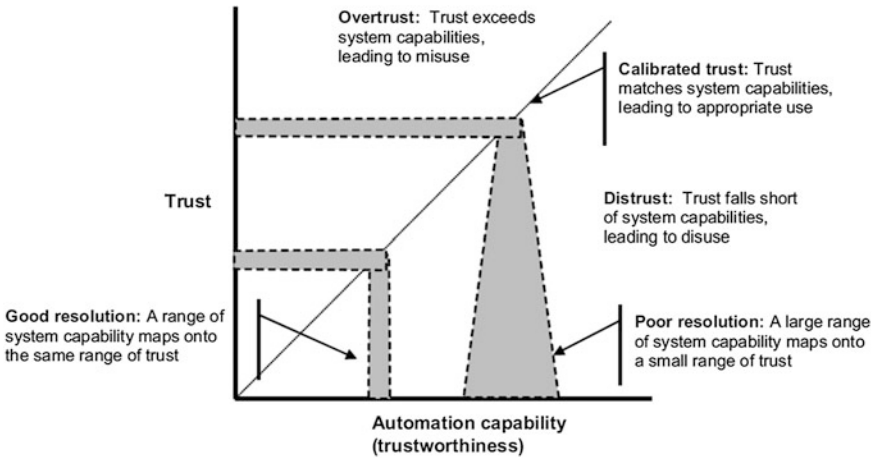

Fig. 3 Relationship between automation capability and user trust [9]. The *diagonal* indicates an appropriate calibration of trust. Areas above and below the diagonal result in overtrust or distrust of the system, respectively

the human-automation team, as it results from a good understanding of the automated system's capabilities. Calibrated trust has good resolution, as a certain range of system capabilities matches with a certain range of user trust. Poor resolution (and poor calibration) results when capability does not match user trust. Parasuraman and Riley [10] provide more insight into the errors committed by human operators with poorly calibrated trust. The authors explain that humans can make inappropriate use of an automated system via misuse or disuse. Misuse refers to detrimental overreliance on the automated system (as when the system is incapable of performing to the operator's expectations). Disuse refers to detrimental underreliance on the automated system (as when the human is incapable of performing to expectations, and needs the automated system to perform better). Thus, a strong H-A team demands that operators have a clear understanding of the automated system's capabilities, and that they understand the situations in which the system's is most useful.

5 Workload Transition: When Automation Fails

Automation failure is not a question of if, but when. If LDSF is to succeed, the H-A system must be capable of handling these failures swiftly, appropriately, and effectively. The point at which automation fails is referred to as a workload transition [11] referring to the transition of workload that was previously managed by the automated system onto the human operator. This process is also euphemistically referred to as an off-nominal event. Understandably, workload transition places a large demand on the human operator, who must now manage not only the automated system's tasks but the repair procedures as well.

The CODDMAN Factors that determine performance of the H-A system after a workload transition are largely related to the design of the automated system itself: going back to the lumberjack effect, a system that is highly automated and has very much responsibility will fail in a more catastrophic way than will a system with less tasking or automation. In addition, as explained earlier, systems that are better understood by their operators are better able to manage workload transitions. However, several human factors affect performance after workload transition, and most of those factors are related to cognitive ability and performance (such as working memory capacity, knowledge of repair procedures, resistance to stress, etc.).

Sebok et al. [12] investigated the process of a workload transition, as well as how various human-automation interaction (HAI) factors were affected by automation at each stage of the information-processing model. The model further considers how fatigue affects various operator tasks and abilities (Fig. 4).

The CODDMAN model [12] provides a simple way of representing a large number of factors that relate to various stages of information processing. In this model, a workload transition occurs between the Detection stage and the Diagnosis stage. Notably, we can see a few of the effects that we have so far covered. System reliability significantly reduces operator monitoring of the system. DOA refers to

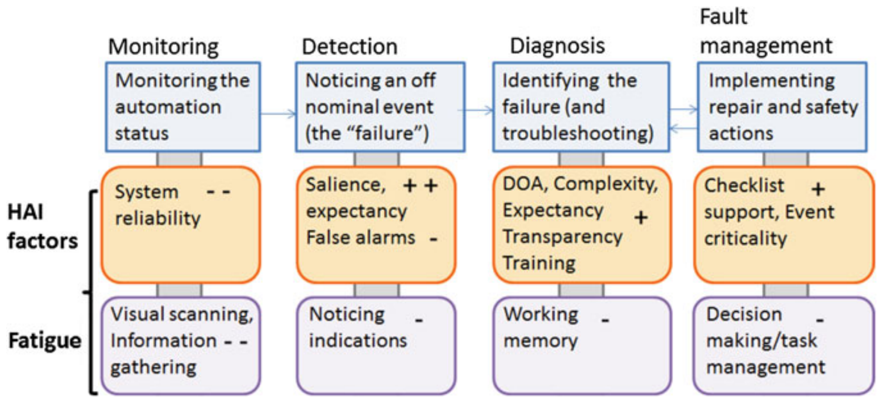

Fig. 4 Complacency Effects on Detection, Diagnosis, and Fault Management (CODDMAN) [12]. Pluses indicate that the relevant stage (e.g. monitoring, detection, etc.) of human tasking is improved by the features with pluses. Minuses indicate that those features reduce the effectiveness of the stage. For the Fatigue row, the effects of fatigue reduce each of the abilities or activities listed in each stage

degrees of automation, and in this case, is not in contrast with the lumberjack effect: rather, this refers to research which has shown that more highly-automated systems (independent of how much responsibility they are tasked with) can provide better support for operators after a failure, which improves fault diagnosis [5]. As a further point, the authors of the CODDMAN model note that the SEEV model [13], which predicts general performance of human operators in multi-modality situations, further validates several of the factors within the CODDMAN model. In sum, each of the factors within the CODDMAN model, and how they relate to the performance of an H-A team undergoing a workload transition, is critical to informing the development of appropriate H-A teams and tasking for LDSF.

6 Conclusions: Designing Automation for Effective H-A Team Performance

We have reviewed several of the factors that affect performance of the H-A team, especially as applied to the context of long-duration spaceflight. In order to prevent or mitigate the risks of off-nominal events, each of these factors must be thoroughly considered during the design of automated systems. Our concluding recommendations for H-A system design are as follows:

1. An automated support system must have an appropriate level of automation so as not to put the team at excessive risk when it fails, in line with the lumberjack effect.

2. The system must be reliable, which will inspire calibrated trust of it by the human operators, which in turn will allow for better performance of the H-A team due to the congruence of their shared mental models.
3. The system should be designed to avoid causing operator misuse or disuse.
4. The system must be designed to allow the operators to swiftly and accurately diagnose and manage faults in the event of workload transition. Such steps may include improving transparency of the system (via improving display ecology), adding checklist support to the fault management step, or improving operator training on system repair and management.

With appropriate consideration of each point, we can give a team of humans with automated assets the best chance to perform to their fullest capabilities and survive the unforgiving demands of LDSF. While LDSF is a special case where the H-A system must be implemented with extreme care, these points can be applied to any H-A system in order to best support the performance of the H-A team.

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