NASA/TM—2017–219565

# Autonomous, Context-Sensitive, Task Management Systems and Decision Support Tools I: Human-Autonomy Teaming Fundamentals and State of the Art

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September 2017

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September 2017

Available from:

NASA STI Program
STI Support Services
Mail Stop 148
NASA Langley Research Center
Hampton, VA 23681-2199

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## Acronyms and Definitions

| | |
|---|---|
| 4D | 4-dimensional |
| AAS | Automation/Autonomous System |
| AC | alternating current |
| ACARS | Aircraft Communications Addressing and Reporting Systems |
| ACAS | Adverse Condition Alerting Service |
| ACAS X | Airborne Collision Avoidance System |
| ACAT | Automatic Collision Avoidance Technology |
| ADS-B | Automatic Dependent Surveillance-Broadcast |
| ASRS | Aviation Safety Reporting System (NASA) |
| ATC | air traffic control |
| ATIS | Automatic Terminal Information Service |
| ATSB | Australian Transport Safety Bureau |
| CASSY | Cockpit Assistant System |
| CDAS | Cognitive Decision Aiding System |
| CDTI | Cockpit Display of Traffic Information |
| CIM | Cockpit Information Manager |
| CSD | cockpit situation display |
| CVS | combined vision systems |
| DARPA | Defense Advance Research Projects Agency |
| DataCom | Data Communications |
| DOA | degree of automation |
| ECAM | electronic centralized aircraft monitoring |
| EGPWS | Enhanced Ground Proximity Warning System |
| EICAS | Engine Indicating and Crew-Alerting System |
| ELP | Emergency Landing Planner |
| EVS | enhanced vision systems |
| FANS | Future Air Navigation System |
| FIS-B | Flight Information Service-Broadcast |
| FMA | flight mode annunciator |
| FMS | Flight Management System |
| GCAS | Ground Collision Avoidance System |
| GPS | global positioning system |
| GPWS | Ground Proximity Warning System |
| HAI | Human-automation/Autonomy Interaction |
| HDD | head down display |
| HMD | helmet mounted display |
| HUD | head-up display |
| HWD | head-worn display |
| IA | intelligent agent |
| IAS | Intelligent Adaptive Systems |
| ITP | in-trail procedure |
| ITWS | Integrated Terminal Weather System |
| LED | light emitting diode |
| LOA | level of automation |
| MATB | Multi-Attribute Task Battery |

MCP ........................................ Mode Control Panel
NASA ...................................... National Aeronautices and Space Administration
NOPE ...................................... non-optimal play environment
NOTAM .................................. Notice to Airmen
NTSB ...................................... National Transportation Safety Board
OCSIS .................................... onboard context-sensitive information system
OFS ......................................... operator functional state
PA ........................................... Pilot's Associate
PBN ........................................ Performance-Based Navigation
PVI ......................................... Pilot-Vehicle Interface
QF ........................................... Quantas Flight
QRH ....................................... Quick Reference Handbook
RNAV ..................................... Area Navigation
ROPS ...................................... Overrun Prevention System pg 26
RPA ........................................ Rotorcraft Pilot's Associate
SA ........................................... situational awareness
SAPA ...................................... Small Aircraft Pilot Assistant
SOP ........................................ Standard Operating Procedure
STL ......................................... Lambert-St. Louis International Airport
SVS ........................................ synthetic vision systems
SWIM ..................................... System Wide Information Management
TAWS ..................................... Terrain Awareness and Warning System
TBFM ..................................... Time Based Flow Management
TBO-AID ................................ Trajectory-Based Operations Adaptive Information Display
TCAS ...................................... Traffic Alert and Collision Avoidance System
TFMS ...................................... Trffic Flow Management System
UAS ........................................ unmanned aerial system
UAV ........................................ unmanned aerial vehicle
USAF ...................................... United States Air Force
XVS ........................................ external vision systems

Autonomous, Context-Sensitive,
Task Management Systems and Decision Support Tools I:
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*Kathleen L. Mosier*[1], *Ute Fischer*[2], *Barbara K. Burian*[3], *and Janeen A. Kochan*[4]

## 1. Introduction

On November 4, 2010, Qantas Flight 32 (QF 32), an Airbus A380 aircraft, experienced an uncontained No. 2 engine failure during climbout after taking off from Singapore Changi Airport (Australian Transport Safety Bureau [ATSB], 2013). Debris from the engine peppered the aircraft and caused wide destruction to a number of the aircraft systems. Over the course of more than 90 minutes the crew responded to a great number of alerts and warnings displayed on the aircraft's electronic centralized aircraft monitoring (ECAM) system, including:

- engines No. 1 and 4 operating in a degraded mode
- low system pressure and low fluid level in the Green hydraulic system
- engine No. 4 Yellow hydraulic system pump errors
- failure of the alternating current (AC) electrical No. 1 and 2 bus systems
- flight controls operating in alternate law
- wing slats inoperative
- partial control of ailerons lost
- spoiler control reduced
- landing gear control issues
- multiple brake system messages
- engine anti-ice and air data sensor malfunctions
- multiple fuel system malfunctions, including a fuel jettison fault
- center of gravity messages
- autothrust and autoland inoperative
- No. 1 engine generator drive disconnected
- left wing pneumatic bleed leaks
- avionics system overheat (ATSB, 2013; p. 170)

Although the crew did a masterful job of completing a successful emergency landing, prior to doing so they spent an inordinate amount of time accomplishing actions associated with the enormous number of ECAM alerts, often being directed to complete the same actions repeatedly, even as the aircraft became more and more out of balance due to a fuel leak. During the subsequent investigation, the crew stated that they eventually decided to dispense with the ECAM action items associated with the multiple malfunctions and instead focus on identifying what was actually working or was serviceable. Only in making this shift in their thinking were they able to develop a

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viable strategy for completing the emergency landing (ATSB, 2013). Although highly capable, the ECAM logic could not evaluate contextual aspects of the situation and adapt the actions presented to the crew for accomplishment accordingly.

Conflicting action demands have hindered crew effectiveness in older-technology aircraft as well. On September 28, 2007, American Airlines flight 1400, an MD-82 aircraft, experienced an engine fire during initial climbout from Lambert-St. Louis International Airport (STL) (National Transportation Safety Board [NTSB], 2009). The fire was the result of an air turbine starter valve that was stuck open and alerted through the illumination of a light in the cockpit. The pilots were not sure how to interpret the visual alert and they made no mention of nor did they access the pertinent abnormal checklist in the aircraft's Quick Reference Handbook (QRH). A few moments after the starter valve light illuminated, the engine fire alert sounded, which appeared to surprise the first officer who had not anticipated that a stuck open starter valve could result in an engine fire (NTSB, 2009). As with the QF32 crew, the American 1400 crew faced multiple systems failures associated with the engine fire, including problems with the hydraulics and electrical systems. In their investigation, the NTSB (2009) determined that these cascading failures were due, in part, to the crew's delay in accomplishing critical items in the Engine Fire/Damage/Separation checklist, such as shutting off the fuel to the engine that was on fire. They interrupted checklist accomplishment several times to attend to other tasks, such as informing the flight attendants of the need to return to STL.

These two events share much in common beyond a critical engine emergency during climbout and subsequent multiple failures involving other aircraft systems. Both were highly stressful and required appropriate prioritization of tasks and distribution of workload. Confusing alerts, interruptions, and distractions were prolific. Developing and maintaining an accurate understanding of the overall situation and responding appropriately to the competing demands encountered in both events was extremely taxing and required the full cognitive resources of all involved.

The management of emergency and abnormal situations has always presented challenges to crews as they have worked to understand their condition and implications for continued safe flight. They have had to quickly grasp the constraints faced—especially the amount of time available—determine and enact the proper response, communicate and coordinate with others as necessary, while still completing other required normal flight tasks. Accident reports across the globe are full of examples of where this has been done well and not so well. As aircraft systems become more and more technologically complex, with tightly coupled autonomous systems responsible for more and more of the flight tasks, the accidents of the future are likely to be similar to these two examples, ones involving multiple systems resulting in an extensive list of failures, confusion, and extremely high workload for the flight crews.

Although workload associated with emergencies such as these can be extreme, even normal operations in today's highly complex and traffic-intense airspace can keep commercial pilots quite busy. Pilots must access and integrate information from a vast array of sources including navigation charts; Notices to Airmen (NOTAMs); Automatic Terminal Information Service (ATIS); aircraft logs and minimum equipment lists; normal checklists; cockpit displays of radar returns, systems status, traffic; and many others as they manage the aircraft automation and their flight path. This workload will only be increased under anticipated reduced crew operations in the future.

For some time aircraft manufacturers and researchers have been pursuing mechanisms for reducing crew workload and providing better decision support to the pilots, especially during non-normal situations (Banks & Lizza, 1991; Champigneux, 1995; Matheus et al., 2005). Some of these approaches, such as increasingly autonomous systems, have indeed reduced workload but have also sometimes had the effect of reducing the pilots' understanding of what the aircraft is doing (Mosier & Skitka, 1996; Sarter, Woods, & Billings, 1997). So too, previous attempts to develop task managers or pilot decision support tools have not resulted in robust and fully functional systems (Banks & Lizza, 1991; Miller & Hannen, 1999). However, the increasing sophistication of sensors and automated reasoners, and the exponential surge in the amount of digital data that is now available create a ripe environment for the development of a robust dynamic task manager and decision support tool that is context sensitive and integrates information from a wide array of on-board and off aircraft sources—a tool that monitors systems and the overall flight situation, anticipates information needs, prioritizes tasks appropriately, keeps pilots well informed, and is nimble and able to adapt to changing circumstances.

In this report, we explore fundamental issues associated with the development of such a system. We discuss information automation and associated human factors issues and review the current state of the art of pilot information management and decision support tools. We explore team behavior and expectations to determine how characteristics of effective human-human teams may be operationalized in teams involving humans and automation or autonomous systems. This report includes a review of critical literature and provides the scientific basis and foundation for the development of a truly robust and highly functional dynamic flight, automation, and information management system. Although much of the report is thus, focused on aviation automation, much of our discussion has relevance for automation and autonomous systems in other domains.

In a companion report (Burian, Kochan, Mosier, & Fisher, 2017) we focus in-depth on constraints and conditions that will drive the functioning and displays of a dynamic flight, automation, and information management system. In this companion report we also explore in great detail the types and sources of data and information that would be integrated into such a system.

As automation and autonomous systems become more and more capable, they have increasingly been imbued with human characteristics including the ability to "assert" themselves as "independent" or at least "quasi-independent" agents (provided they've been programmed as such). Although there is a technical distinction among them, in this document we will use the terms "automation," "autonomous systems," and "agents" interchangeably. We will reserve the use of the term "agent" for highly sophisticated automation and autonomous systems, however, and refer to human actors only as "humans."

## 2. Information Automation

As described above, pilots in current flight operations are required to make sense of a large amount of data and information from a variety of sources including visual cues, instrument readings, information from automated decision aids, and information received from air traffic control (ATC), and to act tactically and strategically to meet multiple and sometimes competing goals. Flight deck operations in the future will depend on a "Net-centric" environment in which information will come from on-board and off-board sources, and many expected innovations to aviation systems will involve information automation (Bailey, Prinzel, Kramer, & Young, 2011).

Information automation is "…devoted to the calculation, management and presentation of relevant information to flightcrew members" (Abbott, McKenney, & Railsback, 2013, p. 40). Although it is typically thought of as distinct from control automation such as an autopilot, it may perform some decision making and action implementation tasks. Information automation monitors relevant data, with associated parameters and/or thresholds fed into dynamic algorithms to identify, "…integrate, summarize, distribute, format, abstract, prioritize, categorize, calculate, process, and display information in a variety of ways to support flight crew tasks" (Letsu-Dake et al., 2015, p. 3D1). In short, it reflects "the programming logic that dictates what information is displayed, when it is displayed, and how it is presented to the flightcrew" (Dudley et al., 2014, p. 296).

The technological capability to deliver almost unlimited information highlights the importance of flight deck systems that "provide the crew with the information they need, when they need it, and with a quality they can trust" (Bailey et al., 2011, p. 9), and to do so without increasing their workload (Abbott et al., 2013; Letsu-Dake et al., 2015). These demands essentially are a call for designing a system that can act like a sensible crewmember, one who perceives information needs and conveys information proactively during the performance of flight tasks. To take up this challenge, a number of fundamental design issues need to be resolved. Insofar as information automation involves the processing of data before they are presented as information to pilots, we need to worry about the appropriate stage and level of data processing. Or put differently, what cognitive processes of pilots—attention, information integration and analysis, option generation—should be supported by information automation? What is the appropriate level of support that information automation should provide? How should information be best presented? Who and what should control the information flow? Additionally, if information automation is to be effective in supporting real-time decisions and actions, it must be sensitive to contextual factors and present information that is relevant to the situation at hand. Which factors should be taken into account to determine the relevance of information? And finally, information automation only 'works' when it is used appropriately. How can system designers ensure that pilots understand and trust the information provided? What human issues and characteristics will impact the use of information automation? These questions outline essential human factors issues in the design and use of information automation.

## 2.1 Human Factors Issues of Information Automation

### 2.1.1 What Cognitive Process Should be Supported?

Mosier and Fischer (2010) introduced the terms 'front end' and 'back end' to characterize different phases of decision making in complex and dynamic environments, such as crew decision making. This distinction is not merely of theoretical significance; rather it is important because human factors applications such as system design or training must be approached very differently depending on the target phase and its related cognitive processes.

The 'front end' (judgment phase) engages cognitive processes concerned with problem identification, information search, problem diagnosis, risk assessment and the evaluation of time constraints (Orasanu, 2010; Orasanu & Fischer, 1997). Related terms are situation awareness and assessment (Durso, Rawson, & Girotto, 2007; Durso & Sethumadhavean, 2008; Endsley, 2000), creating a situation model (Orasanu, 1990), or information acquisition, integration and analysis (Sheridan & Parasumaran, 2006). Several integrated cognitive processes are involved. Problem identification requires perception of and attention to elements in the operational environment, their mental representation, as well as their spatial or temporal relationships. Interpretive processes establish coherent (e.g., causal, temporal, or structural) relationships between elements and relate them to domain knowledge to produce an information-rich and highly structured situation model. The situation model enables pilots to infer causes of events and to predict future developments.

Front-end processes result in a judgment, which may be a rather straightforward evaluation of the initial cue (as when a flight crew judges their fuel remaining as insufficient to reach their destination airport), or it may involve a complex mental representation (as when the crew integrates status indicators from various systems to reach a problem diagnosis; Mosier, 2013). Pilots' judgment about their situation triggers back-end decision processes concerning an appropriate response.

The 'back end' (decision phase) may involve retrieving an appropriate course of action from memory, locating a prescribed response in the appropriate manual, adapting a known response to the specific demands of the current situation, mentally simulating a possible response, planning a sequence of actions, or evaluating alternatives (Mosier & Fischer, 2010; Sheridan & Parasumaran, 2006).

Researchers have argued that information automation is most beneficial if it supports front-end cognitive processes, in particular information acquisition and integration (e.g., Endsley & Kaber, 1999; Sarter & Schroeder, 2001). This recommendation is consistent with models of expert decision making, which describe the decision process as heavily rooted in situation assessment. For example, participants performing an air traffic control-related task exhibited a more accurate situation understanding and superior performance when automated aids supported information acquisition rather than performing cognitive functions such as information integration and analysis (Kaber, Perry, Segall, McClernon, & Prinzel, 2006). Likewise Sarter and Schroeder (2001) report research showing some advantage of displays supporting problem detection and diagnosis as opposed to action selection. During simulated flight, pilots encountered icing conditions. Decision aids either provided information on the location of ice accumulation (=status condition) or specified mitigating actions (=command condition); however, both types of aids could provide incorrect information. Decision aids enhanced pilot performance in both experimental conditions (compared to the baseline condition) when the displayed information was correct. In contrast, when the decision aids provided incorrect information, performance by pilots in the command condition was more negatively affected than the performance by pilots in the status condition. This finding suggests that pilots who are removed cognitively from problem understanding, may "enter a purely reactive mode and blindly follow system recommendations" (Sarter & Schroeder, 2001; p. 581). On the other hand, if pilots are engaged in the process of problem analysis and understanding, they are better able to detect any flaws in action recommendations and are more prepared to intervene as needed.

### 2.1.2 What is the Appropriate Level of Support?

Automated systems can be described in terms of the level of support they provide to human operators. Sheridan (1992) and Endsley and Kaber (1999) both proposed 10 levels of automation that vary from manual decision making and control to complete automation. An inspection of Table 1 reveals a few interesting characteristics of and differences between these taxonomies. First, the two schemes seem to emphasize different aspects of automation. For example, Endsley and Kaber do not make fine distinctions at the high levels of automation, and consider all types of feedback from the system to be equivalent. Instead, they emphasize the lower end of automation by distinguishing how the options are created (i.e., by machine, human, or both). A second interesting observation is that the two schemes are not monotonically compatible. Sheridan's Level 3—'computer offers some alternatives'—resembles Endsley and Kaber's Level 7 'rigid system.'

Table 1. Comparison of Sheridan's Levels of Automation
with the Classification by Endsley and Kaber

| LOW—Low Level Of Automation | |
|---|---|
| *Sheridan (1992)* | *Endsley & Kaber (1999)* |
| 1. Human makes all decisions. | 1. Manual: Human makes all decisions.<br>2. Action support: Computer assists with action.<br>3. Batch processing: Human generates options; selects; computer implements.<br>4. Shared control: Both generate options; human selects; both implement. |
| 2. Computer offers all alternatives.<br>3. Computer offers some alternatives. | 5. Decision support: Computer generates options; human chooses or ignores; computer implements. |
| 4. Computer offers one alternative.<br>5. Computer executes suggestion if approved. | 6. Blended decision making: Computer generates options; computer selects; human consents or chooses or ignores. |
| (3. Computer offers some alternatives). | 7. Rigid system: Computer presents some options; human must select from this list.<br>8. Automated decision making: Computer selects best option from joint list. |
| 6. Computer executes if operator does not veto in time. | 9. Supervisory control: Computer generates, selects, implements action; operator can intervene. |
| 7. Computer executes then informs operator.<br>8. Computer executes and informs when queried.<br>9. Computer executes and informs if computer chooses.<br>10. Computer decides and acts autonomously (full automation). | 10. Full automation: Computer carries out all steps. |
| HIGH –High Level Of Automation | |

Endsley and Kaber (1999) hypothesized that using intermediate levels of automation (LOA) “may provide better human system performance and situational awareness than found with highly automated systems” (p. 483). They examined participants’ abilities to perform a dynamic control task with automation supporting them at each of the levels listed in Table 1. Task performance required participants to: 1) monitor the location, speed and size of targets; 2) generate a situation analysis as well as potential courses of action; 3) select an action;and 4) implement it. Results showed that performance (target collapses, expirations, and collisions) was best under lower LOAs, specifically when humans were involved in situation assessment and generating possible responses, and automation assisted only in implementation. Higher LOAs that provided automated guidance for option selection actually hindered decision making or caused participants to second-guess their judgment. This study is typically cited as providing the rationale for lower LOAs; however, it should be noted that the Endsley and Kaber LOAs do not distinguish between information automation and control automation and, importantly, do not incorporate any variance in automation at the front end of decision making (information acquisition, integration, and analysis).

The concept of LOA was refined by Wickens and colleagues (Wickens, Li, Santamaria, Sebok, & Sarter, 2010) who introduced the notion of degree of automation (DOA). The degree of automation for a given procedure or system/task depends on both the stage of information processing involved and the level of automated support (Onnasch, Wickens, Li, & Manzey, 2014; Parasuraman, Sheridan, & Wickens, 2000, 2008). This characterization may be more appropriate than LOA for the design of information automation because it includes a consideration of the stage of information processing being supported.

Table 2 outlines how automation can provide support for human performance within the four stages of information processing. Moving from lower left to upper right of Table 2, higher levels and later stages (e.g., action automation rather than diagnostic automation) characterize higher DOAs and hence more automation authority and autonomy, whereas lower DOAs imposes greater cognitive and/or motor work on the pilot. Within the columns, higher-level automation means that more integration and synthesis of information is accomplished by the system. Lower levels of automation at each stage keep the operator in the loop by requiring attention, analysis, choice, or acknowledgment and consent.

Table 2. Degree of Automation as the Intersection of Information Processing Stage and Level of Automation

| | Stages of Information Processing | | | |
|---|---|---|---|---|
| | Information Automation | | | Control Automation |
| | Front End | | Back End | |
| *Level* | *1. Perception of/ Attention to Information* | *2. Information Integration* | *3. Decision/ Action Selection* | *4. Action Implementation* |
| Higher | System-specific alert | Suggested diagnosis | Command action (e.g., ‘climb climb’) | Implement autonomously |
| Lower | Alert/alarm | Integrated display | Present choice of action options | Implement after human consent |

Different DOAs have been shown to have different advantages and drawbacks - for example, a command message in the action selection phase (e.g., ‘climb, climb’ in Table 2 above) may elicit quick response, but may not guarantee that the best option is selected. Manual performance of checklist or procedure items keeps the operator engaged and enhances situation awareness (SA), but also imposes high workload on operators, and the operators may skip steps or forget to return to the procedure after an interruption (Wickens 2005; Loukopolous, Dismukes, & Barshi, 2009). Fully automated checklists and procedures, on the other hand, are lower in workload and facilitate speedy and sometimes more accurate performance of steps, but also may foster complacency and automation bias (see below) so that automation errors are not likely to be detected and corrected (e.g., Mosier, Palmer, & Degani, 1992). Additionally, the higher the DOA, the more serious the potential negative consequences can be when automation errs (Onnasch et al., 2014). This is particularly true for the “first failure” off-nominal event that a person may experience with an automation system (Clegg, Vieane, Wickens, Gutzwiller, & Sebok, 2014; Wickens, Hooey, Gore, Sebok, & Koenicke, 2009). Additionally, the DOA is directly related to the allocation of tasks and the extent to which pilots can control task and information flow. These considerations will be important in the design of information automation, as each DOA entails tradeoffs among workload, time (speed of response), and SA.

The concepts of LOA, and by extension DOA, have come under criticism because of their emphasis on function allocation between computers and humans and the relative neglect of the possible ways in which human and machine agents may collaborate (Defense Science Board, 2012). Coactive Design, discussed later, addresses such human and computer collaborations by considering how the capabilities of humans and agents are most effectively combined to meet task requirements.

### 2.1.3 Who is in Charge of Information Flow?

In modern cockpits, specific features of the task, context, and/or automation can predict how pilots will choose to interact with information automation, the type of automation they will use, and the level of support they will select. With a higher degree of information automation, the pilot has lower workload compared to identifying and synthesizing information and making a decision by him/herself. However, high degrees of information automation may also result in decreased awareness and, unless there is system transparency and good feedback, lower predictability concerning the implications of the information and decision for system status or actions. Design questions for information automation include how and when information should be distributed to the pilot, and how functions and tasks should be allocated between the pilot and automation.

***Pushing and Pulling Information.*** Information push and pull are concepts to describe how information resources are distributed to users. “Loosely speaking, if a user requests and receives a very specific piece of information, this is information pull. If information is sent in anticipation of the user’s need, or the agent’s response includes information not directly solicited, then the situation is characterized as information push” (Cybenko & Brewington, 1999, p. 9). Information push has become associated with autonomous agents that may function as intermediaries and perform computational tasks with respect to processing information (Cybenko & Brewington, 1999). Functions of the pushing agent may include locating, filtering, organizing, and alerting information. An issue for information automation is the determination of what information should be constantly displayed, available at operators’ discretion by request (pulled), or made salient to the operator by the automation (pushed). For example, changes in system or situation status or contextual information (e.g., adverse weather conditions) are candidates for information push. Automation should also flag pilot input or actions that are inconsistent with flight plan or current flight context.

***Function Allocation.*** Function allocation is the determination of assignments of work to human and automated agents in a team (Pritchett, Kim, & Feigh, 2014). One early method of function allocation was the Fitts' list approach: Men (or more recently Humans) are better at/ Machines are better at (M/HABA- MABA; Fitts, 1951). The rationale behind this approach was that humans and automation should be allocated the tasks for which they are better suited. For example, because information automation has a larger capacity than human operators for memory and storage, deductive reasoning, and simultaneous operations, many of the data tracking, computational tasks, and alert delivery for fires or malfunctions have been routinely allocated to automation (see also the HART group, 2011).

Fitts' list represented a reasoned approach to function allocation, but is limited in that it is very machine-centered and static (Hoffman & Militello, 2008). More dynamic approaches base function allocation on how tasks can best be shared by humans and automation working together (e.g., Licklider, 1960; Bradshaw, Dignum, Jonker, & Sierhuis, 2012; Bradshaw, Feltovich, & Johnson, 2012). In adaptive systems, the automation controls the division of tasks; adaptable automated systems are adjusted by the operator, who maintains control over automation and is able to designate whether the human or automation will do all or part of tasks (Sheridan & Parasuraman, 2006). Feigh and Pritchett (2014) provided a review of the requirements for effective function allocation, focusing on taskwork functions (performance of activities to meet collective work goals) and their related teamwork functions (communication and coordination among agents). They identified requirements for guiding, measuring, and modeling function allocation that can be used in the design of automated systems.

***Taskwork Requirements*** identified by Feigh and Pritchett consider human issues associated with vigilance and the assignment of authority vs. responsibility. These issues are critical for information automation. In particular, functions should be allocated in so that the human maintains responsibility over automation; that is, the machine may have authority over a function such as providing a decision recommendation, but the human is responsible for overall safety and can override automated suggestions or requirements. Moreover, the collective set of functions (taskload—including monitoring, information integration, or decision making) assigned to an agent cannot exceed the agent's capabilities at any given moment. Automated systems should not create workload spikes—cognitive or manual—for humans, or introduce high interaction demands during off-nominal or emergency situations.

Adaptive approaches to function allocation must also take into account sequential and reciprocal task interdependencies implicit in the distribution of work (see Thompson, 1967), something that is becoming increasingly important from the perspective of human-automation teams. Teamwork requirements suggest that automation should be treated as a team member. Communication between team members is an important component of task accomplishment, and human-human conventions around the timing, interruptive quality, and even politeness of communication should be observed (Dorneich, Ververs, Mathan, Whitlow, & Hayes, 2012; Miller, 2004). As a team member, information automation should be expected to share its rationale for decisions with the human. For instance, in order for the human to approve an action recommended by information automation, he/she needs the system to provide reasoning behind its selection (see Johnson, Bradshaw, Feltovich, Hoffman et al., 2011). Moreover, the human-automation team must have the ability to be resilient, that is, to respond to and cope with dynamic and unexpected situations, and human agents must be able to select strategies appropriate to the situation at hand (Pritchett, 2010; Hollnagel, 1993).

Pritchett, Kim, & Feigh (2014) outlined the metrics to evaluate function allocation including resultant workload/taskload, authority-responsibility mismatches, stability of the work environment, coherence of function allocation, interruptions, automation boundary conditions, system cost and performance, and the humans' ability to adapt to the situational context. Interestingly, these guidelines and metrics imply a consideration of context sensitivity in dynamic function allocation, but do not specify which agent has responsibility for identifying the proper allocation for given contextual variables. Adaptive and adaptable function allocation, which are variations of dynamic function allocation, represent attempts to address this issue (Kaber & Riley, 1999; Kaber, Riley, Tan, & Endsley, 2001; Bailey, Scerbo, Freeman, Mikulka, & Scott, 2003; Miller & Parasuraman, 2007; see also Hancock et al., 2013).

Adaptive and adaptable automation may adjust either the assignment of a task (e.g., the pilot will integrate available information and select a diversion airport or will ask the automation to do so) or the DOA invoked (e.g., the automation will integrate available information and recommend a diversion airport vs. the automation will select the diversion airport and fly the approach). The Playbook approach (Miller & Parasuraman, 2007) discussed in a later section is a form of adaptable automation, in which the human delegates tasks in the form of 'plays' to automated systems. These approaches address some common drawbacks of full automation such as non-vigilance/ complacency/ automation bias threats, manual skill deterioration, loss of SA, and the misuse or disuse of automation, and also address the need for dynamic rather than static allocation of tasks according to user state, required tasks, and the situational context.

Research on degree of automation as well as on function allocation indicates that there is no 'one size fits all' DOA or allocation of tasks. The best design for information automation will be flexible and adaptable. However, some basic guidelines are evident from the research:

1. Information automation should be targeted toward the front end (first two stages) of cognitive processing, providing input for information acquisition and integration. When back-end options/decisions are provided, automation should provide a traceable rationale for these.
2. Keeping the pilot in the loop will be a critical function of future information automation. System design must account for the tradeoff between the speed and efficiency inherent in automation and the loss of pilot awareness when DOA is high. Function allocation must be adaptive to task demands and pilot workload.
3. System design should replicate the capabilities and characteristics of effective human teams; for example, team members should ensure that no one is overloaded, team members should be 'polite' to each other, team members should communicate intentions and goals.
4. System design and task allocation should enable resilience—recovery from unexpected or abnormal states.
5. In order to respond adaptively to dynamic events, automation must be responsive to the situational context.

## 2.2 Context-Sensitive Information Automation

Information automation has to be sensitive to context if it is to be useful and not wantonly increase user workload. Context-sensitive automation is distinct from 'dumb but dutiful' automation (Weiner, 1988, p. 433) whose displays may or may not provide the most relevant information and whose behavior reflects the operative command whether it make sense in the situation or not. Context-sensitive information automation senses and takes into account situational characteristics, and adjusts dynamically in response to them. Context sensitivity requires timeliness, relevance, accessibility, and comprehensiveness of information. A challenge to designers will be to ensure that the right information (relevance and comprehensiveness) is easily available (accessibility) at the right time (timeliness), especially when decisions need to be made under time pressure.

Burian and Martin (2011) discuss the concept of dynamic operational documents, that is, information that is driven by and organized according to specific task demands and aspects of situations or conditions encountered. In their conceptualization, documents such as checklists would be integrated with other types of operational data to support the specific task, anomaly, or situation at hand. Context sensitivity as discussed in this report represents an extension and enhancement of this concept to the broad class of information automation systems. To address safety and operational demands, context-sensitive information automation must take into account flight and aircraft characteristics (e.g., phase of flight, altitude, time, aircraft systems and equipment status, aircraft performance limitations), environmental factors (e.g., weather, smoke, terrain), and existing company policies, procedures and regulations (e.g., SOPs, stable approach criteria), as well as human cognitive and performance variables (e.g., workload, mental models, situation assessment/awareness, memory).

### 2.2.1 Flight and Aircraft Characteristics

Phase of flight is a characteristic that dictates workload (including tasks/procedures to be completed) and time constraints. Departure (takeoff, climb) and arrival phases (approach, landing) are highest in workload and lowest in available time for information acquisition compared with enroute phases. This means that information pushed during those phases (e.g., regarding system failures, traffic) must be highly relevant and easy to comprehend and that non-relevant information should be suppressed. In fact, even some critical alerts, such as engine failures, are suppressed by some alerting systems during these critical high workload phases of flight lest they distract the pilots (Berman et al., in press). Information automation should also be able to sense equipment failures or system problems, as well as links and dependencies among aircraft systems and take these into account when integrating or displaying operational information or recommended actions. Automation databases must incorporate the performance characteristics and limitations of the aircraft, so that information can be tailored to these as well. If the pilot does not have a realistic assessment of what actions can be taken and what the aircraft can do, the effectiveness of his or her response to a situation may be constrained or misguided. For example, in the US Airways 1549 landing on the Hudson, information automation did not alert Captain Sullenberger that his pitch control inputs were restricted by the aircraft systems, giving him the illusion that he could exert more nose-up control than was actually possible (Harris, 2007).

### 2.2.2 Environmental Factors

Environmental factors are also part of the context. Inside the aircraft, conditions such as smoke, decompression, or toxic fumes generate the need for specific behaviors and actions. Externally, weather-related factors such as precipitation, icing, air pressure, or turbulence will impact both the information needed by the operator and the actions that can be taken. Limitations imposed by ground variables such as terrain, obstacles, or airport status and runway conditions must be integrated and made available or pushed to the pilot as needed.

### 2.2.3 Policies, Procedures, and Regulations

Current operational documents (electronic or paper) such as checklists, manuals, or Standard Operating Procedures (SOPs) provide pilots with information structured around airline and federal flight operation policies and regulations. Some of these prescribe requirements that apply across general situational contexts—for example, the criteria for a stable approach—and this information should be integrated with current flight parameters so that pilots can be informed of discrepancies and deviations. Other types of documents are more context-dependent, such as a non-normal checklist with several branches, as was the case in the US Airways 1549 landing in the Hudson (NTSB, 2010). One purpose of context-sensitive information automation, such as dynamic checklists, would be to eliminate non-relevant branches or information searches (e.g., what is my altitude?) and facilitate accurate and timely completion of procedures (Burian, 2014).

### 2.2.4 Human and Cognitive Performance Variables

A primary purpose of context-sensitive information automation is to facilitate the development of situational awareness (SA) and accurate situational mental models. This means it must be designed with consideration for human cognition and cognitive factors that impact performance, how people identify and make sense of a situation, and how they develop accurate mental models of systems and situations. As discussed earlier, supporting the front-end processes of information acquisition and analysis/ integration will be most effective in terms of SA and the development of mental models, and also keeps the operator in the loop (e.g., Endsley & Kaber, 1999; Sarter & Schroeder, 2001).

Context-sensitive information automation must also take into account other factors that impact performance such as workload, psychophysiological state, or experience. For example, adaptations in information automation should occur with changes in task demands or operator functional state (OFS, physiological signals; Wilson & Russell, 2003a,b). Additionally, the system should sense and suppress non-relevant information during high-workload phases such as takeoff or landing, or perhaps would synthesize information and make different types of recommendations according to pilot variables such as fatigue.

Proper weight and value must be given to these various factors to ensure that the information automation displayed at any moment is properly prioritized relative to the context encountered. The constraints and conditions associated with context-sensitive information automation prioritization and display are explored in more depth in the companion document to this report (Burian, et al., 2017).

### 2.2.5 Quality, Usability, and Integrity of Context-Sensitive Information Automation

***Timing of Information.*** The value of information provided by automation is directly related to its timeliness and 'freshness' as well as to its contextual relevance. Information automation must incorporate real-time sensing of information needs. Pilots will need all information related to a particular task, situation, or phase of flight soon enough to incorporate it into decisions, etc., but not so early as to induce premature closure on SA or resultant actions. Additionally, 'stale' information, such as outdated weather forecasts or airport status data, is not only *not* useful, but it also may be hazardous if pilots use it to plan their actions.

***Information Sources.*** Data for context-sensitive information automation may come from different sources such as sensors, databases, algorithms, or data entered by the pilot or ground. It is imperative that, regardless of the source, data must be as specific, accurate, reliable, accessible, comprehensive, and timely as possible. Additionally, information automation must be transparent concerning the limitations of its data, so that pilots know which elements it cannot sense or calculate (e.g., the presence of birds or large animals on the runway, or data whose validity may be suspect).

***Resilience.*** Resilience is a construct that has been discussed with respect to organizational and socio-technical systems as well as to physical (e.g., automation hardware and software) systems. Four basic concepts have emerged from within different technical approaches: 1) resilience as *rebound* from disruption/harm; 2) resilience as *robustness*; 3) resilience as *graceful extensibility* of boundaries rather than brittleness; and 4) resilience as architectures that are *adaptable* to unforeseen events (Woods, 2015).

Importantly, information automation systems must be robust and resilient enough to facilitate, rather than hinder performance during non-normal or emergency situations. Early, and some current, automation has been described as 'brittle,' that is, it addresses a limited set of pre-specified situations, has little or no capability to learn, and fails catastrophically when it reaches its limits rather than degrading gracefully and obviously (e.g, Bainbridge, 1983; Pritchett, Kim, & Feigh, 2014; Thurman, Brann, & Mitchell, 1997). Resilient systems, in contrast, are able to prevent or adapt to changing conditions, avoid failures and losses through anticipation, recover from disruptions—especially those that are not within the set of abnormalities the system is built to handle—and maintain control over properties such as safety or risk within the larger socio-technical system (e.g., National Airspace) or the physical system (e.g., automation on the aircraft) itself (Leveson et al., 2006; Madni & Jackson, 2009; Woods & Hollnagel, 2006). Resilience is a key component of context-sensitive information automation, as it must be able to respond to dynamic normal and non-normal situations.

## 2.3 Design Issues

Although sophisticated software technology enables collection of vast amounts of information, possibilities for visual information display are constrained by so-called "real estate" limitations; in other words, the number and size of screens and indicators in a cockpit, information that is dedicated or reserved for different displays or parts of displays, and ergonomic considerations about where the displays are placed on the flight deck. Additionally, the most effective information display mode—visual, aural, tactile—must be determined. Human limitations in terms of attention, visual and auditory overload, and processing must be considered in the design of information automation. Information display format (e.g., gauges, numbers, graphics, symbols, text) and coding (e.g., type and length of audible or tactile alarms, localization within the flight deck) should also enable the pilot to track its source and reasoning, and should elicit the appropriate cognitive response.

Each of the issues discussed below must be considered with respect to its individual resolution (e.g., how to make information salient, which mode to use, etc.) and also with respect to its impact on the overall system. Design features that improve one system, for example, may add complexity, contribute to loss of SA, or increase the probability of errors (Ahlstrom & Longo, 2003).

### 2.3.1 Salience

The salience of information automation is a key determinant of attention and use. Salience in turn is related to automation compellingness (Dorneich et al., 2015; Dudley et al., 2014). Pilots (as most people) are inclined to pay attention to salient cues, such as stick shakers, or visual and aural alarms (Dismukes, Berman, & Loukopoulus, 2007). Central placement, bright lights, or aural disruptions elicit and concentrate the attention of the pilot and these design decisions have implications for what information is attended to. Salience, however, has a flip side: on one hand, it is essential to the compellingness and thus the attention to information; on the other hand, salient information automation may engulf or overwhelm other necessary information, curtailing situation assessment and leading to possible errors (Mosier & Skitka, 1996; see also section on Automation Bias).

### 2.3.2 Display Placement and Mode

One of the challenges for information automation is avoiding potential visual overload, as most such data are acquired visually. This is particularly important with respect to status changes and warnings. The failure of pilots to notice mode transitions and mode changes, for example, may be due to their visual display, which is not preemptive enough to command the crew's attention (Wickens, 2003; also see Salience above). Other examples of inadequate information display include presentations in which related information is scattered across different displays or checklists, critical information is insufficiently highlighted or buried, or displays that are so cluttered that discerning relevant information is difficult.

Experiments using various display technologies have been geared toward identifying pilot perceptions and characterizations of display clutter and influences of display clutter on pilot performance (e.g., Alexander, Stelzer, Kim, Kaber, & Prinzel, 2009; Kaber, Alexander, Stelzer, Kim, & Hsiang, 2008; Kim et al., 2011). Some results indicate there may be a clutter "threshold" beyond which pilot performance degrades (Kaber et al., 2008), suggesting that advanced technologies that increase display clutter may be counter-productive,and pointing to the need to both eliminate clutter and improve the salience of critical symbology and information (e.g., Naylor, Kaber, Kim, Gil, & Pankok, 2012).

One solution to visual overload is the employment of other sensory modalities. Warnings or alarms presented in the auditory modality are effective in interrupting ongoing visual monitoring in the electronic cockpit (Stanton, 1994; Wickens & Liu, 1988), and do not add to the array of data and information that must be absorbed visually. For example, a typical traffic alerting system such as TCAS (Traffic Alert and Collision Avoidance System) uses aural alerts as the level of potential danger rises, and a combination of visual and auditory commands if it detects that the likelihood of collision is high (Wickens, 2003). Three-dimensional localized auditory alerts, which place the origin of the alert spatially in the cockpit corresponding to the location of the traffic threat outside the aircraft, have also been found to result in faster traffic detection than conventional head-down displays (Begault & Pittman, 1996). Feedback may also be distributed across modes of presentation or provided in the tactile mode. For example, the stick shaker is a traditional tactile warning of impending aerodynamic stall. Sklar and Sarter (1999) found that tactile cues were also better than visual cues for detecting and responding to uncommanded mode transitions.

Other display solutions involve changing the format and accessibility of visual cues and information. For example, the head-up display (HUD) superimposes symbology representing aircraft trajectory parameters (e.g., altitude, airspeed, flight path) on the pilot's external view (e.g., Pope, 2006), enabling easy monitoring of both electronic and naturalistic cues and information. Head-worn displays (HWDs) providing augmented reality (i.e., spatially-integrated symbology and imagery) have been proposed as essential elements for a Better-Than-Visual operational concept (Bailey et al., 2011).

### 2.3.3 Transparency and Accessibility vs. Opaqueness and Layers

Providing sufficient information and transparency in displays while avoiding cognitive overload is a difficult task. However, automation visibility, that is its transparency and the feedback it provides on its sources and functioning (Dorneich et al., 2015), is a key determinant in whether pilots will trust information automation, as will be discussed below. Moreover, design decisions concerning the placement of visual information (e.g., electronic flight bags vs. primary displays vs. secondary displays) and its accessibility (e.g., surface vs. layered or hidden) will impact how and how well flight crews can use visual information automation. Many cockpit displays represent hidden stores of complex data, highly complex combinations of features, options, functions, and system couplings that may produce unanticipated, quickly propagating effects if not analyzed and taken into account (Woods, 1996). Decision support systems, in particular, may often present only what has been deemed "necessary," making it difficult for pilots to monitor them and assess their accuracy (in judgment) and adequacy (of decision). Data are pre-processed, and presented in a format that allows, for the most part, only a surface view of system functioning, and precludes analysis of the consistency or coherence of data. Information automation that provides this type of synthesis removes the pilot from the diagnosis phase, and lack of transparency precludes the capability to track its processes (e.g., Woods, 1996; Sarter, Woods, & Billings, 1997).

Part of the problem with lack of transparency is that information calculations and resultant commands/actions often occur without the awareness of the human operator. Moreover, system status may not be clear because within many displays are numerical data that signify different commands or values in different aircraft, phases of flight, or modes. Pilots may not have sufficient knowledge about system functioning to recognize or understand potential consequences of specific mode selections, or may be confused about what aircraft behaviors to expect (Abbott et al., 2013). For example, mode confusion was a factor in the Strasbourg A-320 accident in which pilots flew a -3300 ft/min descent into a mountain. In this situation, the cockpit setup for a flight path angle of -3.3 deg in one flight mode looks very much like the setup for a -3300 ft/min approach in another flight mode (Ministre de l'Equipement, des Transports et du Tourisme, 1993).

### 2.3.4 Display Format and Interpretation: Intuition vs. Analysis

A key element in display design is that performance depends on the degree to which task properties elicit the most effective cognitive response (Hammond, Hamm, Grassia, & Pearson, 1997). Characteristics of information display (e.g., graphical vs. text) will facilitate or hinder pilots' effective cognitive processing of it. For example, the graphic representations that exploit human intuitive pattern-matching abilities and enable quick detection of some out-of-parameter system states are compatible with and facilitate intuitive cognition. However, they may also set up the false expectation that the electronic cockpit can be managed solely via intuitive cognition (Mosier, 2008). Pilots who rely on intuition when analysis is required—as when information is presented textually or numbers must be calculated, integrated, or compared—may miss important data as well as the implications of these data.

Information automation display format must match the cognitive mode required to synthesize and use the information. Formats that elicit intuitive and holistic processing, such as pictures or symbols, should not require analysis for interpretation and understanding. Displays that rely on the use of text or numbers should not be used when quick recognition or understanding is needed, as they reduce the ability to use intuition or to pattern-match and increase the need for analytical processing (Mosier & McCauley, 2006).

## 2.4 Psycho-Social Issues: Trust, Complacency, and Automation Bias

The willingness of the human team member to use information provided by an automated agent and allocate tasks to automated systems depends to a great extent on the psycho-social variable *trust*, which is impacted by system properties and performance as well as system understandability and transparency. Trust can facilitate appropriate use of information automation—or may lead to complacency and resultant errors characterized as automation bias.[5]

### 2.4.1 Trust in Automation

A key component in human-automation interaction is the extent to which the operator trusts the system (e.g., Chen & Barnes, 2014; Lee & See, 2004). Bailey and Scerbo (2007), for example, found an inverse relationship between trust and monitoring performance. Moreover, the development of complex autonomous systems has heightened the importance of trust in human-automation teaming (Schaefer, Chen, Szalma, & Hancock, 2016). Not surprisingly, antecedents and outcomes of trust in automation have received much research attention. Early taxonomies of trust characterized the antecedents in terms of predictability, dependability, and faith (Muir, 1994). Similarly, Lee and his collaborators (Lee & Moray, 1992; Lee & See (2004) described the factors that form the bases of trust as *performance* (what the automation does and its competence), *process* (how the automation operates and the appropriateness of its algorithms), and *purpose* (why the automation was developed and extent to which its use is consistent with its purpose).

A review by Hoff and Bashir (2015) provides a synthesis of the empirical research on trust in automation between 2002-2013. They characterized antecedents of trust into three categories: 1) *Dispositional trust* or personal trust factors include personality traits, age, gender, and culture; 2) *Situational trust* factors include internal, context-dependent characteristics of the operator such as self-confidence, subject matter expertise, mood, and attentional capacity, as well as external environment variables such as type and complexity of system, task difficulty, workload, perceived risks and benefits, the framing of a task, and the organizational setting; and 3) *learned trust* factors are a combination of initial trust, which incorporates preexisting knowledge about a system based on attitudes, experiences, system reputation, and one's understanding of a system, and dynamic learned trust, a function of system performance—it's reliability, validity, predictability, dependability, error types and timing, and usefulness, and design features such as transparency/feedback, and level of control (Hoff & Bashir, 2015). Of these, learned trust variables discussed below are most fundamental for system design.

***Performance, Capability, and Reliability.*** In general, findings across many studies suggest that automation reliability is strongly associated with trust development and maintenance, and that

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[5] In addition to an individual human operator's trust in automation and autonomous systems, the trustworthiness of human-automation teams (as a team) and the quality of their joint decision-making has also been of interest to the computing and artificial intelligence communities for a number of years (e.g., Taylor & Reising, 1995). Although important, this issue is outside the scope of this manuscript.

operators adjust their trust in automation in line with its performance (Hoff & Bashir, 2015). Experience with reliable automated systems increases trust; negative experiences with automation can reduce it (Manzey, Reichenbach, & Onnasch, 2012). For example, participants using an automated decision aid to identify the presence or absence of a camouflaged soldier were more likely to rely on the aid when it was more reliable than manual operation, and conversely were less likely to trust and rely on it when it was less reliable than they were (e.g., Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003). Moreover, the reliability/performance of one facet of a system (e.g., one gauge or indicator) has been found to have 'contagion effects,' influencing operator system-wide trust (Geels-Blair, Rice, & Schwark, 2013).

Interestingly, different error types can differentially and over time impact trust, reliance, and compliance with information automation. Automation *misses* (failures to detect a signal or problem) vs. *false alarms* (incorrect alerts or directives) affect whether and how operators rely on the system and what facets of the system they trust. A high number of automated alert misses, for example, led participants to under-rely on automation during normal periods (they did not trust it to detect anomalies and alert them to abnormal events) and to over-rely on system alarms (they always trusted that system alarms that *did* occur were 'real'). In contrast, a prevalence of *false alarms* affected participant compliance with the system. Operators trusted the automation to catch system anomalies (it would not miss an event) but did not automatically comply with alerts (because they did not trust that all of the alerts they received were 'real;' Sanchez, Rogers, Fisk, & Rovira, 2014). Lees and Lee (2007) also found that false alarms decreased trust and compliance levels; however, when the alarm was viewed as unnecessary rather than false (e.g., the automation viewed the situation as more hazardous than the human), trust and compliance actually increased.

Similar patterns were noted in a series of studies by Dixon and Wickens (2003, 2004, 2006). Participants in a multi-task unmanned aerial vehicle (UAV) simulation were required to detect system failures with the help of an imperfect automated aid. The researchers found that participants adjusted their interaction with the system according to its primary failure mode. When the system gave many false alarms, participants began to ignore alarms, thus missing true indications of system failures. When the system exhibited a pattern of missed failures, participants paid more attention to the gauges (raw data), but neglected secondary tasks. Also, participants responded to alarms more quickly in a mostly misses condition than in a false alarms condition, suggesting that they were not verifying the alarms. Additionally, the difficulty of automation's assigned task is a factor in trust. When automation errs on a task that the human perceives as easy, trust is likely to decrease—but not if the task is perceived as difficult (Madhavan & Wiegmann, 2007; Madhavan, Wiegmann, & Lacson, 2006).

Overall, system predictability and dependability are critical to sustained trust. When the human operator experiences expected and predictable automation actions and interactions, trust builds and continues (e.g., Cahour & Forzy, 2009). If the human operator experiences unexpected or erroneous behaviors from automation, trust is likely to drop and automation use is likely to decrease or information provided by the automation may be disregarded or disused (Weigmann, Eggman, ElBardissi, Parker, & Sundt, 2010).

***Understandability and Transparency.*** Early in the evolution of automation, experts cautioned that we must guard against pilots' misconception of systems, especially concerning the connections between subsystems and built-in assumptions that drive system behavior. Billings (1996) emphasized the need to train pilots *how systems operate* rather than simply *how to operate systems*:

“If a pilot does not have an adequate internal model about how the computer works when it is functioning properly, it will be far more difficult for him or her to detect a subtle failure. We cannot always predict failure modes in these more complex digital systems, so we must provide pilots with adequate understanding of how and why aircraft automation functions as it does” (p. 96). Operators must have sufficient knowledge of what new automated systems can do, what they “know,” and how they function within the context of other systems, as well as knowledge of their limitations, in order to utilize them efficiently and exploit their real capabilities. When operators’ mental models of system functioning are not accurate, especially with respect to eliciting attention to relevant task elements for situation awareness, the credibility of the system and thus operator trust in it is likely to decrease (Fogg & Tseng, 1999; Sarter, Woods, & Billings, 1997).

Key antecedents to the development and calibration of system trust are system understandability and transparency (e.g., Chen, Barnes, & Harper-Sciarini, 2011; Lyons et al, 2016; Sheridan, 1988). Lyons et al. (2016) varied the transparency of an Emergency Landing Planner (ELP; Meuleau, Plaunt, Smith, & Smith, 2008) in terms of the rationale it gave for its recommendations: risk-based transparency, logic-based transparency, and control (baseline output; no rationale). Pilots flew diversion scenarios using each of the transparency conditions. Pilots’ trust was highest in the logic condition and lowest in the control condition, and they also expressed a strong preference for the logic condition. In other work, Dzindolet et al. (2003) demonstrated that providing explanations for automation failures can increase trust. These results suggest that operators want explanations from automated systems, a notion that is supported by the finding that operators trust high-level automation to take over functions more readily when it provides information to the operator than when it does not (Verberne, Ham, & Midden, 2012).

Letsu-Dake et al. (2015) suggested that complex systems should provide support for learning how they work, and also for verifying their reasoning. They conducted a low-fidelity simulator human-in-the-loop study to assess the impact of automation functional complexity in terms of number and diversity of automation functions, inter-relationships and inter-dependencies, and intricacy of processing, and automation visibility in terms of transparency and feedback on state, information sources, and how information is being used, on oceanic in-trail procedures (ITPs). Pilots flew experimental scenarios under conditions of high complexity with high automation visibility (manual concept), low complexity with high visibility (semi-automated concept), and low complexity with low visibility (fully automated concept) ITP displays. Pilots preferred the automated displays, and made correct decisions using the fully automated display, took less time to generate an ITP clearance, and reported lower workload with this display compared with the others. The authors’ recommendations for design of information systems included the suggestion for help functions so that pilots could learn the functionally complex automation systems during non-critical situations, and the notion that easier to use, less complex systems may in some cases be better than more complex systems even though they are less capable. With respect to automation visibility, they recommended that information for verification of system reasoning and output should be available and easy to detect and access. The authors called for an evaluation of the tradeoffs between information presentation to facilitate understanding of automation state and potential increases in pilot workload to process the information.

In related work, Dorneich and colleagues (Dorneich et al., 2015) showed that automation information visibility, operationalized as automation providing a rationale for recommendations, affected pilots’ perceptions of automation awareness and of trust while it did not did not influence the quality of their decisions. When information quality was low (e.g., its reliability was questionable, it was not relevant, or it was untimely), trust was related to automation visibility, increasing with higher visibility. When information quality was high, however, visibility did not influence perceptions of trust; participants trusted the automation whether or not it provided a rationale for its recommendations. Similar to Letsu-Dake et al. (2015), the authors noted potential tradeoffs between facilitating understanding of automation by providing additional information and the additional workload required to process the information.

A recent meta-analysis assessed antecedents of trust in automation (Schaefer et al., 2016), broken down into human-, automation-, and environment-related factors. The findings supported earlier research suggesting that automation capabilities are important predictors of trust. They also found evidence of the importance of cognitive, emotive, and demographic human-related factors in automation trust development, including features of automation such as communication modes and aesthetics.

Other relevant points from studies in the Schaefer et al. meta-analysis are:

- the LOA that is perceived as appropriate ("good") fosters greater trust than a LOA that is deemed "poor" or "ambiguous" (Merritt, Heimbaugh, LaChapell, & Lee, 2013)
- operators prefer and exhibit more trust in automation that is collaborative and provides explicit control to the human (i.e., over function allocation) (e.g., Moray, Inagaki, & Itoh, 2000; Sauer, Nickel, & Wastell, 2013)
- anthropomorphism impacts trust in complex automation, such as intelligent agents or robots (Pak, Fink, Price, Bass, & Sturre, 2012)
    - human speech is preferred and trusted over synthetic speech (Stedmon et al., 2007)
- trust is impacted by the appropriateness of cues and feedback, such as their accuracy and truthfulness (Sharples et al., 2007; Spain & Bliss, 2008), and their ability to communicate effectively (e.g., Stanton, Young, & Walker, 2007)

Recently de Visser and his colleagues (2016) examined human trust of automation as a function of the degree to which the automated agent appeared and behaved like humans. They found, as have others (Pak et al., 2012), that increased anthropomorphic features (e.g., an avatar with human appearance) and behavior of the agent (e.g., apologizing for mistakes) resulted in greater human trust and trust resilience (i.e., ability to retain or repair trust that has been negatively impacted by faulty agent suggestions). It should be noted, however, that participants in the de Visser et al. experiments were naïve undergraduates. Whether their findings would replicate in a sample of pilots with substantial automated systems experience has yet to be tested.

### 2.4.2 Automation-Related Hazards Influenced by Trust

The downside of designing information automation that fosters trust is that the development of *too much* trust in the system will have potential negative consequences. Since the introduction of automated systems in aviation, a key challenge has been getting operators to use these systems appropriately. Parasuraman and Riley (1997) outlined the hazards of what they termed automation misuse (overreliance on automation) and disuse (underutilization or neglect of automation). Of these, automation misuse is documented more frequently than disuse among professional pilots, most often taking the form of automation induced *complacency* manifested in inadequate monitoring and/or non-vigilance, or *automation bias* resulting in missed problems or poor decision making. These phenomena represent unintended consequences of trust in automated systems. These challenges to appropriate automation use become more important to resolve as more sophisticated and reliable automation is introduced into the cockpit.

***Complacency.*** Automation-induced complacency typically stems from over-trust in automation and inattention, and may be exacerbated by experience with highly reliable automation (Parasuraman & Manzey, 2010). It is a flawed monitoring strategy, and is characterized by a low level of suspicion, non-vigilance and sub-standard monitoring behavior, and an assumption of satisfactory system state (Dzindolet et al., 2003; Parasuraman & Manzey, 2010). Some researchers have used eye-tracking measures to examine how often operators look at displays (e.g., Metzger & Parasuraman, 2005; Sarter, Mumaw & Wickens, 2007) as a measure of complacency. Complacency is not always overt, making it difficult to assess, and insufficient vigilance rarely leads to problems because systems perform very reliably. In fact, some have argued that people should only be expected to monitor systems at a rate that is consistent with their reliability—that doing so represents good calibration with the system (Moray, Inagaki, & Itoh, 2000). This seems like a reasonable idea; however, when dealing with extremely reliable aircraft automation, this calibration method would result in almost no monitoring at all.

Parasuraman and his colleagues conducted a program of research to define characteristics of automation-induced complacency using the MATB (Multi-Attribute Task Battery) (e.g., Parasuraman, Molloy, & Singh, 1993; Singh, Molloy, & Parasuraman, 1993a,b, 1997; Singh, Sharma, & Parasuraman, 2001). Findings suggested that people are more likely to exhibit complacency when they are in a multi-task environment with consistently and highly reliable automation than when in performing a single monitoring task or with lower or variable reliability automation (Parasuraman et al., 1993; see also Bagheri & Jamieson, 2004). Changing the location of the monitoring task so that the display was more focally located did not eliminate complacency-related errors (Singh et al., 1997).

Several studies have documented complacency in experts working with automated systems. Pilots, for instance, were less likely to detect engine malfunctions and air traffic controllers were less likely to detect conflicts when performing these tasks with automated support versus manually (e.g., Galster & Parasuraman, 2001; Metzger & Parasuraman, 2005). Complacency is so prevalent that it is a coding item in Aviation Safety Reporting System (ASRS) reports, and is an acknowledged contributor to airline accidents and incidents.

***Automation Bias.*** A related negative outcome of experience with reliable automation has been referred to as automation bias, a flawed decision process characterized by the use of automated information as a heuristic replacement for vigilant information seeking and processing (Mosier & Skitka, 1996). Two classes of automation-related errors commonly emerge in highly automated cockpits: 1) omission errors, defined as failures to respond to system irregularities or events when automated devices fail to detect or indicate them; and 2) commission errors, which occur when decision makers incorrectly follow an automated directive or recommendation. Commission errors are the product of premature closure and a curtailed decision process—operators follow automation recommendations without verifying their accuracy or appropriateness. For example, Layton, Smith, and McCoy (1994) examined pilot use of a graphical flight planning tool, and found that computer generation of a suggestion or recommendation early in the course of problem evaluation significantly impacted decision processes and biased pilots towards the computer's suggestion, even when the computer's brittleness (e.g., in terms of an inadequate model of the "world") resulted in a poor recommendation with potential adverse consequences. Likewise, Mosier and colleagues

(Mosier, Skitka, Heers, & Burdick, 1998) found that all of the pilots in a flight simulation study shut down a working engine based on a faulty Engine Indicating and Crew-Alerting System (EICAS) engine fire alert that was not supported by any other cockpit indicators.

Information automation provides a powerful, authoritative, salient cue that may overshadow less prominent information, and trust in these systems, as discussed, is fostered by their high reliability. The use of automation as a short-cut may be encouraged by other features as well, such as an opaque interface that does not facilitate understanding and tracking of system functioning (Sarter, Woods, & Billings, 1997; Woods, 1996). Automation bias may also stem from a belief in automation as a relative 'authority' in decision processes, leading people to follow automated recommendations without questioning them. Abbott et al. (2013) noted that pilots' confidence in automation may make them reluctant to intervene. Moreover, organizational or regulatory policies may mandate reliance on automated information and directives over other sources as is the case with GPWS (Ground Proximity Warning System) or TCAS (Traffic Collision Avoidance System) aural and visual displays.

High workload may exacerbate the tendency toward automation bias. The Dorneich et al. (2015) study discussed earlier found that air transport pilots tended to over-trust an information automation system when they were under high workload and chose the top plan suggested by the system, even though information was missing and the plan was not the best one (see Vicente, 2003 for similar human-automation findings in the health care domain). Additionally, poor information quality was found to degrade pilots' decisions, apparently as a result of automation over-reliance. In these instances, pilots did not notice that automation failed to consider critical information.

***Phantom Memory and Looking-But-Not-Seeing.*** An interesting finding from two Mosier et al. flight crew studies was a phenomenon they dubbed "phantom memory" (Mosier et al., 1998; Mosier, Skitka, Dunbar, & McDonnell, 2001). Pilots in one- and two-person crews tended to erroneously "remember" the presence of expected cues confirming the presence of an engine fire, thus supporting their subsequent decision to shut down the supposedly affected engine. The phenomenon highlights the fact that pilots may not be aware of contradictory information even when the evidence is in front of them. Interestingly, two crews in the 2001 study left the engine running and available – and these crews knew and reported that no other indicators were present. A related effect was found by Manzey et al. (2008), who measured the time that participants spent "looking at" verification information for automation failures. Those who avoided a commission error spent more time looking at the information than those who committed the error. Manzey hypothesized that those who committed the error did not absorb the information from other indicators. He discussed this as a "looking-but not seeing" effect. Similarly, Sarter et al. (2007) noted that pilots often did not grasp mode changes even when they fixated on the flight mode annunciator (FMA). These findings suggest that it is critical to ensure that pilots not only attend to but also absorb and comprehend the information they are given by automated systems.

***Mitigating Complacency and Automation Bias.*** A key issue for mitigating complacency and automation bias is whether associated errors result solely from an attentional lapse (Parasuraman & Manzey, 2010) or whether they are the result of some flawed decision—to delegate to the automation, to follow the automation, etc. (Mosier & Skitka, 1996). The source of automation-related errors has implications for design and interventions to resolve this issue. Interventions for attention lapses, for example, might be rooted in improving monitoring behavior, or calling attention to specific automation behaviors. Interventions for a decision bias, on the other hand, may focus on improving information use and decision making.

Automation bias shares roots with other decision heuristics and biases. For example, pilots or operators may 'see' automated information they expect to see (expectation-driven processing, as in 'phantom memory' described above), or discount information that does not support their preferred plan (e.g., plan continuation errors; confirmation bias), or base their evaluation of automated information in terms of similar situations in recent memory (availability; for a review of heuristics and biases in flight crew decision making, see Mosier, Fischer, & Orasanu, 2011). Training and design solutions for automation bias could capitalize on successful strategies from the heuristics and biases literature, such as accountability interventions.

The imposition of pre-decisional accountability for decision processes has been shown to effectively mitigate many decision biases including automation bias. When pilots and people in general know that they are accountable for (e.g., have to explain or justify) their decision processes, they exhibit more effortful monitoring and vigilant information seeking, more complex data processing, and more consistent patterns of cue utilization (e.g., Hagafors & Brehmer, 1983). In sum, accountability increases vigilance in decision making and increases the tendency to use all available information for situation assessment. In the Mosier et al. (1998) study, professional pilots who reported higher levels of accountability for their automation strategies and a stronger need to justify their interaction with the automation were more likely to double-check automation functioning against other cues and were less likely to commit errors. Other related work has also demonstrated the effectiveness of requiring verification behaviors as a mitigation strategy (e.g., Bahner, Huper, & Manzey, 2008; Reichenbach, Onnasch, & Manzey, 2010; Skitka, Mosier, & Burdick, 2000).

Without training or design interventions, complacency and automation bias are not likely to disappear in future cockpits. Clearly, psycho-social issues of trust, complacency, and automation bias must be taken into account in the design of new automated systems. Information automation must elicit trust and at the same time provide safeguards against complacency and automation bias. This means that the systems must provide high-quality, accurate, and timely information, and do so reliably and transparently. Transparency in design will also enable verification behaviors to avoid complacency and automation bias. As a guard against complacency, automation should be adaptable by the pilot (i.e., the pilot can assign tasks and change the level of automation) and adaptive to situational context (e.g., high workload phases of flight). Additionally, procedural and design safeguards should be implemented to ensure that pilots attend to and comprehend important information.

# 3. Current Information Automation

Current and future flightdeck operations depend on a "Net-centric" environment in which information comes from on-board and off-board sources, and expected innovations to aviation systems will involve even more comprehensive information automation than is available today (Bailey et al., 2011). Below we provide brief descriptions of some of the information automation enhancements that are in use or are being introduced to facilitate pilot decision making. Comprehensive definitions and descriptions of these NextGen concepts can be found in:

- Federal Aviation Administration (2015). *NextGen Implementation Plan 2015*. Office of NextGen. Retrieved from: https://www.faa.gov/nextgen/media/NextGen_Implementation_Plan-2015.pdf
- NextGen, NextGen Priorities Joint Implementation Plan (2014). Executive Report to Congress. Retrieved from: https://www.faa.gov/nextgen/media/ng_priorities.pdf
- RTCA NextGen Integration Working Group Final Report (2014). Report of the NextGen Advisory Committee in Response to a Tasking from the Federal Aviation Administration. Retrieved from: http://www.rtca.org/Files/Miscellaneous%20Files/NextGen_Integration_Working_Group_Report_Oct_2014.pdf

## 3.1 Enhanced Vision Systems

Enhanced vision systems can provide increased visibility, symbology, and information for enhanced situation awareness and reduced pilot error, improvements in low-visibility operations, and overall enhanced pilot performance, particularly in terminal operations.

*Cockpit Situation Displays (CSDs)* present information about surrounding aircraft to the flight crew. This information includes the relative positions, speeds, and trajectories of these aircraft, as well as 'conflict' alerts when another aircraft is expected to approach too closely. CSDs provide a volumetric representation of the surrounding three-dimensional traffic environment and integrate 3-dimensional weather information into the interface.

*Enhanced Vision Systems (EVS)* are electronic means to provide a display of the forward external scene topography (the natural or manmade features of a place or region, especially in a way to show their relative positions and elevation) through the use of imaging sensors, such as a forward looking infrared, millimeter wave radiometry, millimeter wave radar, or low light level image intensifying. During an instrument approach, the enhanced vision image is intended to enhance the pilot's ability to detect and identify visual references for the intended runway.

*Synthetic Vision Systems (SVS)* provide a computer generated image of the external scene topography and render terrain elevation data oriented in real-time to aircraft attitude and altitude.

*Combined Vision Systems (CVS)* concept involves a combination of synthetic and enhanced systems. The CVS includes database-driven synthetic vision images combined with real-time sensor images superimposed and correlated on the same display. This includes selective blending of the two technologies based on the intended function of the combined vision system. For example, on an approach, most of the arrival would utilize the SVS picture. As the aircraft nears the runway, the picture gradually and smoothly transitions from synthetic to enhanced vision, either for SVS picture validation or displaying the runway environment.

*External Vision Systems (XVS)* such as external cameras bring information to the cockpit from various positions outside the aircraft, such as taxi cameras.

*Head up displays (HUD*s), head down displays (HDDs), head worn displays (HWDs), helmet mounted displays (HMDs) and other monocular and binocular displays are used by pilots to view enhanced vision system information combined with flight path displays.

### 3.2 Terrain Avoidance

*Ground Proximity Warning System (GPWS)* provides aural and visual alerts for terrain avoidance.

*Terrain Awareness and Warning System (TAWS)* (also known as Enhanced Ground Proximity Warning System [EGPWS]) uses aircraft inputs such as position, altitude, air speed, glideslope and flight plan along with internal terrain and airport databases to predict a potential conflict between the aircraft's future flight path and terrain.

*Automatic Collision Avoidance Technology (ACAT)* is a tool designed for a smartphone as an assisted automatic ground collision avoidance system. ACAT steers the aircraft away from the ground or mountains by using global positioning system (GPS), accurate ground maps, and a connection to the aircraft flight controls. The technology could help prevent controlled-flight-into-terrain accidents by general aviation and unmanned aircraft.

*Automatic Ground Collision Avoidance System (Auto GCAS)* detects an imminent impact with terrain, and temporarily takes control of the aircraft and executes an automatic recovery maneuver.

### 3.3 Traffic Conflict Avoidance

*Cockpit Display of Traffic Information (CDTI)* presents ground (aircraft and ground vehicles) and airborne proximal traffic location, status and flight plan data. It incorporates strategic conflict detection and alerting, automated conflict resolution strategies, provides the ability to graphically plan manual route changes and shows time-based, in-trail spacing on approach.

*Traffic Alert and Collision Avoidance System (TCAS)* monitors traffic, alerts the crew to potential conflicts and provides escape route displays.

*Airborne Collision Avoidance System (ACAS X)* is a TCAS system with the capability to adapt to different kinds of aircraft and minimize nuisance alerts in the projected higher density traffic areas of NextGen (e..g, terminal areas).

*ASDE-X and Traffic Information Service – Broadcast (TIS-B)* capture surface activity (taxi and airport surface).

*Automatic Dependent Surveillance-Broadcast (ADS-B)* in and out provides information on ground and flight traffic.

*NextGen Airport Traffic Situation Awareness with Indications and Alerts (SURF-IA)* provides flight deck indications and alerts of potential or actual traffic conflicts on or near the airport surface. SURF-IA graphically highlights traffic or runways on an airport moving map to inform flight crews of detected conditions that may require their attention. Additional auditory attention getting cues are provided for non-normal, hazardous situations to allow flight crews to immediately respond to potential runway safety hazards.

*NextGen Time Based Flow Management (TBFM)* includes decision support tools designed to increase efficiency through separation-related maneuvers initiated by either Air Traffic Control or the pilot.

### 3.4 Navigation

*Area Navigation (RNAV)* provides precise flight path specification and monitoring.

*NextGen Performance-Based Navigation (PBN)* tools such as Integrated Arrival Airspace Management and Time-Based Metering using metering automation provides increased capacity and closely spaced and curved approaches.

*Trajectory-Based Operations Adaptive Information Display (TBO-AID)* (Bruni, Jackson, Chang, Carlin, & Tesla, 2011; Bruni, Chang, Carlin, Swanson, & Pratt, 2012) provides information necessary for pilots to follow a 4-dimensional (4D) trajectory while maintaining separation from other aircraft and weather.

*Future Air Navigation System (FANS)* is designed to aid flight crews in the use of Trajectory-Based Operations without increasing workload (e.g., Coppenbarger, Mead, & Sweet, 2009).

### 3.5 Flight Planning and Route Deviations

*NextGen Collaborative Air Traffic Management* tools include full flight plan constraint evaluation with feedback, interactive planning using 4D trajectory information in the oceanic environment and interactive flight planning from anywhere. Users (dispatchers and pilots) will have access to information regarding traffic density and real-time weather allowing for flight planning activities to be accomplished from the flight deck or a ground station. Airborne and ground automation provide the capability to exchange flight planning information and negotiate flight trajectory agreement amendments in near real-time.

*NextGen Traffic Flow Management System (TFMS)* provides flight data and flow information.

The *Emergency Landing Planner (ELP)* by Meuleau et al. (2008) supports "…rapid analysis of complex situations, including damage to the aircraft, adverse weather, and status of possible landing sites to recommend a safe route and desired approach" (Lyons et al., 2016).

### 3.6 Weather

*4D Weather Data Cube* enables quick filtering of the weather content to the region and timeframe of interest.

*Flight Information Service-Broadcast (FIS-B)* provides additional airspace status and weather information.

*Predictive Airborne Windshear Warning Systems* monitor wind data, detect windshear, provide pilots alerts and flight guidance to escape the encounter.

*Adverse Condition Alerting Service (ACAS)* provides pilots alerts of new adverse conditions specific to their filed flight plans via text, email and Iridium satellite devices. The alerts prompt pilots to obtain additional weather information.

*NextGen System Wide Information Management (SWIM) Integrated Terminal Weather System (ITWS)* provides specialized weather products in the terminal area such as alerts, configured by the user, for weather hazards in the terminal area.

*Lockheed Martin Departure Planning Tool* is an example of a graphical summary of weather conditions along a route of flight for proposed departure times with the optimum time (based on weather forecasts) highlighted for the pilot.

### 3.7 Communication

*Aircraft Communications Addressing and Reporting System (ACARS)* enables communication with ground operations and reporting of flight progress.

*Data Communications (DataComm)* is a datalink communications technology that enables the uploading of flight plans and changes, as well as strategic trajectories and trajectory negotiation.

### 3.8 Pilot Awareness and Decision Support

*Engine Indicating and Crew-Alerting System (EICAS) or Electronic Centralised Aircraft Monitor (ECAM)* provides integrated engine and system status information and generates alerts for parameters out of tolerance. In some cases, EICAS or ECAM information will include checklists with tasks to be accomplished.

*Master Caution/Master Warning and other Alerts* intend to gain pilots' attention and focus it on an off-nominal situation.

*NextGen Full Collaborative Decision Making* tools support stakeholder decisions through access to an information exchange environment and a transformed collaborative decision making process that allows wide access to information by all parties (whether airborne or on the ground). Decision-makers request information when needed, publish information as appropriate, and use subscription services to automatically receive desired information through the net-centric infrastructure service.

*NextGen On-Demand NAS Information* is collected from both ground systems and airborne users, aggregated, and provided via a system-wide information environment in near real-time and in a user-friendly digital or graphic format (e.g., ForeFlight, JeppFD, GarminPilot, etc.).

*Overrun Prevention System (ROPS)* is designed to continuously calculate whether an aircraft can safely stop in the runway length remaining ahead of the aircraft. If at any point the system detects there is a risk of a runway overrun, flight deck alerts are generated to help the crew in their decision making. The system has access to the parameters which affect an aircraft's stop distance.

The areas in which these technologies provide different aspects of front-end or back-end decision support, as well as their level and type of automation are indicated in Table 3. Most, though not all (e.g., many checklists, ACARS) almost by definition are sensitive to the context (e.g., CDTI, ELP, EGPWS). However, it is difficult to rate or indicate how each fare relative to the many design or psycho-social issues discussed (e.g., salience, transparency, engendering trust), in part because the same type of technology from different manufacturers may be designed and function differently. Therefore, design features and psycho-social issues are not included in the table.

Table 3. Function and Qualities of Current Information Automation
("X" indicates element is present)

| | Decision Support: Front End | | | | | Decision Support: Back End | | | | Level of Automation | | Function Allocation | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Information Automation Tool | Information Search | Problem Identification/ Diagnosis/ Analysis | Information Integration | Risk Assessment | Evaluation of Time Constraints | Guiding Decision Making/Action Execution | Planning Actions | Adapting Response to Situation | Evaluation Alternatives | Sheridan (1992)1 | Endsley & Kaber (1999)2 | Adaptive | Adaptable |
| **Enhanced Vision Systems** | | | | | | | | | | | | | |
| *Cockpit Situation Display* | X | X | X | X | X | X | X | X | X | 5 | 6 | | X |
| *Enhanced Vision Systems* | X | | X | | | | | | | 1 | 1 | | |
| *Synthetic Vision Systems (SVS)* | X | | X | | | | | | | 1 | 1 | | |
| *Combined Vision System (CVS)* | X | | X | | | | | | | 1 | 1 | X | |
| *External Vision Systems (XVS)* | X | | X | | | | | | | 1 | 1 | | |
| **Terrain Avoidance** | | | | | | | | | | | | | |
| *Ground Proximity Warning System (GPWS)* | X | X | X | X | X | X | | X | X | 4 | 6 | | X |
| *Terrain Awareness and Warning System (TAWS)* | X | X | X | X | X | X | X | X | X | 4 | 6 | | X |
| *Automatic Collision Avoidance Technology (ACAT)* | X | X | X | X | X | X | X | X | X | 10 | 10 | X | |

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| Table 3. Function and Qualities of Current Information Automation (continued) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Decision Support: Front End | | | | | Decision Support: Back End | | | | Level of Automation | | Function Allocation | |
| Information Automation Tool | Information Search | Problem Identification/ Diagnosis/ Analysis | Information Integration | Risk Assessment | Evaluation of Time Constraints | Guiding Decision Making/Action Execution | Planning Actions | Adapting Response to Situation | Evaluation Alternatives | Sheridan (1992)1 | Endsley & Kaber (1999)2 | Adaptive | Adaptable |
| Traffic Conflict Avoidance | | | | | | | | | | | | | |
| *Cockpit Display of Traffic Information (CDTI)* | X | X | X | X | X | X | X | X | X | 4 | 8 | | X |
| *Traffic Alert and Collision Avoidance System (TCAS)* | X | X | X | X | X | X | X | X | X | 4 | 8 | | X |
| *Airborne Collision Avoidance System (ACAS X)* | X | X | X | X | X | X | X | X | X | 4 | 8 | | X |
| *ASDE-X and Traffic Information Service – Broadcast (TIS-B)* | X | X | X | X | X | | | | | 1 | 1 | | X |
| *Automatic Dependent Surveillance-Broadcast (ADS-B)* | X | X | X | X | X | | | | | 1 | 1 | | X |
| *NextGen Airport Traffic Situation Awareness with Indications and Alerts (SURF-IA)* | X | X | X | X | X | | | | | 1 | 1 | | X |
| *NextGen Time Based Flow Management (TBFM)* | X | X | X | X | X | X | X | X | X | 3 | 5 | | X |
| Navigation | | | | | | | | | | | | | |
| *Area Navigation (RNAV)* | X | | | | | | | | | 1 | 1 | | X |
| *NextGen Performance-Based Navigation (PBN)* | X | X | X | X | X | | | | | 1 | 1 | | X |
| *Trajectory-Based Operations Adaptive Information Display (TBO-AID)* | X | X | X | X | X | X | X | X | | 3 | 5 | | X |
| *Future Air Navigation System (FANS)* | X | | X | | | | | | | 1 | 1 | | X |

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Table 3. Function and Qualities of Current Information Automation (continued)

| | Decision Support: Front End | | | | | Decision Support: Back End | | | | Level of Automation | | Function Allocation | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Information Automation Tool | Information Search | Problem Identification/ Diagnosis/ Analysis | Information Integration | Risk Assessment | Evaluation of Time Constraints | Guiding Decision Making/Action Execution | Planning Actions | Adapting Response to Situation | Evaluation Alternatives | Sheridan (1992)1 | Endsley & Kaber (1999)2 | Adaptive | Adaptable |
| Flight Planning and Route Deviations | | | | | | | | | | | | | |
| *NextGen Collaborative Air Traffic Management* | X | X | X | X | X | X | X | X | X | 4 | 6 | | X |
| *NextGen Traffic Flow Management System (TFMS)* | X | X | X | X | X | | X | X | X | 3 | 4 | | X |
| *The Emergency Landing Planner (ELP)* | X | X | X | X | X | X | X | X | X | 4 | 8 | | X |
| Weather | | | | | | | | | | | | | |
| *4D Weather Data Cube* | X | X | X | | X | | | X | | 1 | 1 | | X |
| *Flight Information Service-Broadcast (FIS-B)* | X | | X | | X | | | | | 1 | 1 | | X |
| *Predictive Airborne Windshear Warning Systems* | X | X | X | X | X | X | X | X | X | 4 | 8 | | X |
| *Adverse Condition Alerting Service (ACAS)* | X | X | X | X | X | | | | | 1 | 1 | | X |
| *NextGen System Wide Information Management (SWIM) Integrated Terminal Weather System (ITWS)* | X | X | X | X | X | | | | | 1 | 1 | | X |
| *Lockheed Martin Departure Planning Tool* | X | X | X | X | X | | X | X | X | 3 | 5 | | X |

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| Table 3. Function and Qualities of Current Information Automation (continued) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Decision Support: Front End | | | | | Decision Support: Back End | | | | Level of Automation | | Function Allocation | |
| Information Automation Tool | Information Search | Problem Identification/ Diagnosis/ Analysis | Information Integration | Risk Assessment | Evaluation of Time Constraints | Guiding Decision Making/Action Execution | Planning Actions | Adapting Response to Situation | Evaluation Alternatives | Sheridan (1992)1 | Endsley & Kaber (1999)2 | Adaptive | Adaptable |
| Communication | | | | | | | | | | | | | |
| *Aircraft Communications Addressing and Reporting System (ACARS)* | X | | X | | | | | | | 1 | 1 | | X |
| *Data Communications (DataComm)* | X | | X | | | | | | | 1 | 1 | | X |
| Decision Support | | | | | | | | | | | | | |
| *Engine Indicating and Crew-Alerting System (EICAS) or Electronic Centralised Aircraft Monitor (ECAM)* | X | X | X | | | X | X | X | | 4 | 6 | | X |
| *NextGen Full Collaborative Decision Making* | X | X | X | X | X | | X | X | | 3 | 7 | | X |
| *NextGen On-Demand NAS Information* | X | X | X | X | X | | X | | | 3 | 7 | | X |
| *Overrun Prevention System (ROPS)* | X | X | X | X | X | X | X | X | X | 4 | 8 | | X |

[1] Sheridan (1992): 1=Human makes all decisions, 2=Computer offers all alternatives, 3=Computer offers some alternatives, 4=Computer offers one alternative, 5=Computer executes suggestion if approved, 6=Computer executes if operator does not veto in time, 7=Computer executes then informs operator, 8=Computer executes and informs when queried, 9=Computer executes and informs if computer chooses, 10=Computer decides and acts autonomously.

[2] Endsley & Kaber (1999): 1=Manual, human makes all decisions, 2=Action support, computer assists with action, 3=Batch processing, human generates options, selects, computer implements, 4=Shared control, both generate options, human selects, both implement, 5=Decision support, computer generates options, human chooses or ignores, computer implements, 6=Blended decision making, Computer generates options, computer selects, human consents or chooses or ignores, 7=Rigid system, Computer presents some options, human must select from this list, 8=Automated Decision making, computer selects best option from joint list, 9=Supervisory control, Computer generates, selects, implements action, operator can intervene, 10= Full automation, computer carries out all steps.

# 4. Current Approaches to Information Management

The automated tools above are precisely that—individual or separate tools—and their capability to function as part of a human-automation team is limited. Although some systems provide information or feedback automatically, in many cases, the pilot still has to elicit and integrate information to build a mental model of the situation. This is changing as newer information systems such as ADS-B, FIS-B, weather, and decision support provide integrated information to flight crews as well as to the ground.

Some approaches to information management have taken a more proactive approach to aiding pilot decision making and come closer to the notion of context sensitivity and the qualities of an automated team member. The level of authority and allocation of functions varies in different systems discussed below, but each of them includes some level of intelligent automation, shared mental models, and collaboration between human and automated team members. Lessons learned from the conceptual underpinnings of the systems as well as from their successes and shortcomings should be incorporated in the design of context-sensitive information management automation.

## 4.1 Supervisory Control vs. Interdependent Team Members

When the concept of levels of automation was first introduced, the assumption generally was that the human (operator or designer) would allocate tasks to automated machines and the operator would monitor them (Johnson, Bradshaw, Feltovich, Hoffman, et al., 2011; Sheridan & Verplank, 1978)—what is known as a supervisory control model. The human is the initiator and supervisor of activities. In the automated cockpit, for example, the pilot inputs commands via the FMS (Flight Management System) or MCP (Mode Control Panel)—sometimes via an iPad™ link—and the selected system follows instructions, while the pilot monitors aircraft behavior to ensure the commands are being carried out. Many information management and decision support tools follow this model, such as Playbook (Miller & Parasuraman, 2007). Associate System Technology, such as the Pilot's Associate (Miller & Hannen, 1999), aids decision making by performing ground-work tasks of information acquisition and integration, enabling the pilot to make better decisions. Banbury, Gauthier, & Scipione (2007) conducted a literature review on Intelligent Adaptive Systems (IAS) developed to that date. We discuss the most relevant of these systems, including Playbook and Pilot's Associate.

A more recent approached enabled by current technological advances treats human and automated agents as interdependent team members who share a common mental model of situations and goals and can coordinate and collaborate activities, monitor each other, provide feedback to each other, and adapt dynamically to contextual demands (e.g., Bradshaw, Dignum, et al., 2012; Hancock et al., 2013; Johnson, Bradshaw, Feltovich, Jonker, et al., 2011). This approach is characterized as Coactive Design, and is also discussed below.

### 4.1.1 Playbook

The *Playbook* approach (Miller, Goldman, Funk, Wu, & Pate, 2004; Miller & Parasuraman, 2007) is a supervisory control implementation of adaptable automation involving human driven determination of the level of automated support (vs. adaptive automation—system driven determination). The notion is to create a shared task model between humans and automation, and enable operators to delegate tasks and subtasks to automation and to receive feedback about the system's performance. This enables flexibility in the level of automation (LOA) and role of automation during system operations and minimizes the workload associated with choosing a LOA.

Playbook is rooted in the sports analogy of a coach creating specific maneuvers ahead of time. These maneuvers/procedures are 'plays' that can be called and then carried out autonomously. Plays are templates of plan and behavior alternatives that are predetermined and vary in complexity and control authority (Miller et al., 2004; Shively, Flaherty, Miller, Fern, & Neiswander, 2012). When using Playbook with automated systems, the human calls the plays, but automation shares responsibility, authority, and autonomy for whatever division of labor the human has selected (via the play). The system may also inform the human about the feasibility or infeasibility of potential plays (for instance, insufficient fuel) and whether the play combinations will accomplish the end goal. Plays can be at varying levels of complexity and inclusiveness, representing different LOAs. An example would be the choice of a diversion airport—the play could specify that the automation stays at the level of providing information about options, or could trigger the automation to recommend and implement a diversion plan.

Demonstrations of Playbook's efficacy have been conducted primarily with unmanned aerial vehicles/systems (UAV/UAS) and tactical mobile robots (Parasuraman & Miller, 2006; Miller & Parasuraman, 2007; Shively and colleagues, see section on UAS and Robotics Research below) and in general support the notion that delegating tasks through plays provides improved SA, lower workload and better performance. One advantage of the Playbook strategy is that it can be used by a single operator to control multiple UAVs or mobile robots at once while maintaining low workload. It seems to be a promising technology for multiple-entity control automation, as long as the desired 'plays' can be identified ahead of time. However, Playbook is not context-sensitive; nor can it be proactive in identifying the appropriate level of plays to be engaged.

### 4.1.2 Pilot's Associate

One well-known example of a knowledge-based, intelligent decision support system is the Pilot's Associate (PA) approach (Banks & Lizza, 1991; Miller & Hannen, 1999). Initiated in 1986 by the Defense Advanced Research Projects Agency (DARPA) and the U.S. Air Force, the Pilot's Associate program was envisioned to provide fighter pilots with a fully integrated system that could support both front-end and back-end processes of their decision making as well as the execution of actions. Subsequently this concept was adapted to assist U.S. Army Rotorcraft pilots (Rotorcraft Pilot's Associate; RPA).

An associate system is typically comprised of a "collection of aiding systems that, collectively, exhibit the behavior of a capable human" (Miller & Hannen, 1999). One set of the subsystems assesses the external world and the status of aircraft systems. Information from these situation assessment modules feeds into planning systems, and vice versa, planning modules can direct situation assessment. Planning subsystems suggest responses to immediate threats and necessary adjustments to the pre-briefed mission plan. Situation status, threats and appropriate responses are displayed on an intelligent user interface, called "Pilot-Vehicle Interface" (PVI) in the U.S. Air Force's (USAF) version of the Pilot's Associate (USAF PA; Banks & Lizza, 1991), and "Cockpit Information Manager" (CIM) in the U.S. Army's Rotorcraft (RPA) version (Miller & Hannen, 1999).

The intelligent user interface is the centerpiece of the associate concept. It is via this interface that the associate shares task- and mission-critical information with the pilot, and to a limited extent, the pilot is able to "communicate" with the system—capabilities that require the capacity to synthesize situational information, knowledge of plans and mission goals, and an understanding of user needs. The intelligent user interface in both the PVI and the CIM fulfill three functions:

1. *Information Management*. The interface determines what information is presented to the pilot, and in which format; that is, only information and recommendations are pushed that are pertinent to active plans, and consistent with pilots' intentions and situation assessment subsystems.
2. *Intent Estimator*. The interface is capable of inferring pilots' intentions based on their actions, mission goals and current situation.
3. *Adaptive Aiding*. The interface assists pilots in task management, identifies and flags inconsistent pilot actions and proposes error remediation.

Human-automation interaction in the PA approach involves shared—in the sense of 'distributed'—responsibility; the pilot's role is one of supervisory control as he/she can vary the level or extent of assistance. That is, pilots determine the nature of the associate's backup behavior, either prior to a mission or during a mission in response to changing situational demands. They may task automation with information acquisition and analysis, and the PA, in return, will provide information judged to be useful for them at that moment in time. Pilots may also authorize the associate to select and execute action plans (Banbury, Gauthier, & Scipione, 2007). Once responsibilities are assigned to the associate, it will perform them without further pilot input or direction. For instance, in one simulation the PA detected a fuel transfer failure, determined that the problem was a stuck fuel valve, and based on pre-mission authorization by the pilot, toggled the fuel valve and informed the pilot about the corrective action (see Banks & Lizza, 1991).

Common ground between pilots and the associate consists of shared knowledge about mission plans and goals that pilots enter into the system prior to mission. During the mission, updates to plans, goals, as well as user and situation models are provided by the automation, given pilot authorization. The PA's performance monitoring involves the identification of pilot actions that the system cannot explain on the basis of its task and situation model. In the Air Force's version of the PA this process is unidirectional; that is, it is established by the automation without direct pilot feedback. Pilots can express their disagreement with the system's situation assessment and user model by ignoring suggestions generated by the PA; however, they cannot change the PA's situation and user model nor access or query the basis for its assessments. The RPA, in contrast, "includes an interface that "provide[s] the crew with both insight into, and some control over, CIM's understanding of their intent" (Miller & Hannen, 1999, p. 450-451). Separate light emitting diode (LED) buttons display "in text, the current inferred (1) high-level mission context, (2) highest priority pilot task, (3) highest priority copilot task, and (4) highest priority CDAS [= Cognitive Decision Aiding System] task. Pressing these buttons permits the pilot to override CIM's current inferred tasks and assert new ones via push button input" (Miller & Hannen, 1999, p. 451).

Both the RPA and the USAF PA monitor the flight situation via reasoning algorithms that differ from the cognitive processes underlying pilots' situation assessment. For example, the Pilot Information Requirement module assigns values between 0 and 10 to a set of parameters, such as importance or scope, to determine the information a crewmember needs for a given task. As a result, pilots may have difficulties retracing the system's understanding and verifying its coherence (Svenmarck & Dekker, 2003). Common ground between pilots and the associate may be further impeded by limited system transparency. While the associate presents assessments and suggestions, it is not designed to provide reasons for them, nor are pilots able to request clarification as they could if they were to interact with a human team member.

Evaluations of the PA concept in simulated missions revealed that pilots generally appreciated the system's information management (Miller & Hannen, 1999; Svenmarck & Dekker, 2003), and rarely disagreed with actions suggested by the associate (Miller & Hannen, 1999). Pilots also reported that the associate generally helped to reduce their workload. However, in situations characterized by rapidly changing task priorities and needs, pilots' workload increased as they shifted responsibilities to the associate (USAF, 1995 reported in Svenmarck & Dekker, 2003).

Increases in pilot workload during highly dynamic flight situations may in part be due to the fact that interactions between pilots and the associate rely exclusively on visual information. The availability of voice communication could facilitate human-automation interaction, especially in situations in which automation needs to direct the pilot's attention to pertinent information and vice versa, when pilots want to pull information from the system not included in its situation model. For instance, a pilot assistant developed in Germany, the Cockpit Assistant System (CASSY; Gerlach & Onken, 1995) combines text-based communication and visual displays with spoken communication via voice synthesizer and speech recognition.

The PA was designed to assist pilots with situation assessment and decision making. However, by presenting its understanding of situation together with recommended responses, the PA may lead to complacency or automation bias in pilots, especially since pilots have no means to access and thus verify the reasoning of the system.

### 4.1.3 Other Information Management Systems for Transport and Military Aircraft

A different approach than those described was planned for the Copilote Electronique, for use in French military aircraft and operations (Champigneux , 1995; Joubert et al., 1995). The Copilote Electronique was conceived of as a "high level dialogue function between man and machine" (Champigneux, p. 5-2) to support the pilot in reflecting on his/her situation assessment thus stimulating self-critiquing. This on-board knowledge based system was to serve first as a gatherer and processor of large quantities of "raw" information and then, most crucially, as a filter so that only information deemed pertinent is presented to the pilot, along with a restricted set of action choices to choose among (Joubert et al., 1995). Following action selection, the Copilote Electronique would evaluate all possible consequences of the action prior to execution. Thus, it would differ from previous tools in that it not only would provide context-sensitive information but also determine which of a large range of possible actions might be appropriate and guide the pilot to that restricted list. Additionally, an evaluation of the consequences of an action would be conducted by the system *following* selection, perhaps because the highly dynamic nature of military operations might render an action acceptable one second but unacceptable a few seconds later. At this point, very little information about the Copilote Electronique is available in the published literature and it is unknown if it was ever developed and, if so, to what level of maturity.

Tan and Boy, in loose collaboration with the aircraft manufacturer Airbus and others, have undertaken a more recent attempt to develop an onboard context-sensitive information system

(OCSIS) for transport category aircraft (Tan, 2015). Although intended to integrate information from a variety of printed flight deck documents (e.g., dispatch guides, minimum equipment lists, operations manuals), the current, early stage prototype is centered solely around context-sensitive normal checklists and checklists for response to a select set of non-normal/ emergency conditions. The system was developed for display and use on a tablet (such as an Apple iPad™ ); however flight parameters synchronously transferred from the simulator drive its dynamic functionality. In terms of its overall functionality, the early prototype of OCSIS is still quite brittle and limited in terms of its responsiveness to events but shows some potential promise.

### 4.1.4 Small Aircraft Pilot Assistant

Future airspace will include many more and more sophisticated small, single-pilot aircraft than is the case today, as described in the Small Aircraft Transportation System Higher Volume Operations concept (Abbott, Jones, Consiglio, Williams, & Adams, 2004). The Small Aircraft Pilot Assistant (SAPA) is a decision aid system for single-pilot general aviation aircraft. Its goal, similar to the PA, is to facilitate pilot decision making by automating part of the decision process – specifically the stages of information acquisition and analysis (Rong, Spaeth, & Valesek, 2005). The system uses artificial intelligence techniques such as Fuzzy Logic and Expert Systems to identify flight status information, traffic and traffic conflicts, and pilot performance and potential errors. Based on flight status, the Pilot Advisor module determines what advisory and alert messages should be displayed to the pilot, and the Pilot Interface Manager determines how to present the information. The Conformance Monitor module is able to sense flight conformance with the planned flight segment and inform the pilot of conformance violations.

Another advantage of this system is that it is designed for single-pilot operations, which are likely to be extended in future to larger aircraft. Preliminary tests suggest that the will be effective in supporting single-pilot decision making; however, more research on the appropriate level of automation as well as the prioritization of warning and advising messages from multiple situation assessment modules is needed (Rong et al., 2005).

### 4.1.5 Digital Copilot

The Digital Copilot, recently developed by the MITRE Corporation (Estes et al. 2016), is another example of a cognitive and task support tool developed specifically with general aviation single pilots in mind. As its name implies, the Digital Copilot is intended to reduce a pilot's workload by providing some of the same assistance that a human copilot might provide. Through a speech recognition based interface, the Digital Copilot can respond to a limited set of factual pilot queries using published information and estimations of aircraft performance, such as whether or not a destination airport tower will be open when the aircraft arrives.

The Digital Copilot also spontaneously provides speech notifications intended to increase the pilot's situation awareness. Such notifications include automatically providing Automatic Terminal Information Service (ATIS) information when within a certain distance of a destination airport and the amount of runway remaining during takeoff, among others. The Digital Copilot currently includes 25 "cognitive assistance features" derived through 10 algorithms used to infer a pilot's intent and provide context-sensitive and relevant information to reduce pilot workload (Estes et al., 2016). As with the SAPA, if-then and fuzzy logic as well as Bayesian probabilities form the basis of the algorithms.

Initial testing in a modified flight simulator has shown that the Digital Copilot has some promise for reducing general aviation single-pilot workload. However, some pilots have expressed concern that the autonomously provided aural notifications may misinterpret pilot intent or be distracting, undesired, or ill timed (K. Ruskin, K. Dismukes, personal communication September 2016). More research is needed, particularly in busy airspace with a lot of radio chatter and demanding flight tasks, to determine the degree to which these potential issues are valid.

### 4.2 Coactive Design

Coactive Design is a recent approach to system design that takes as its starting point the interdependent relationships of human and machine agents during joint activity (Johnson, Bradshaw, Feltovich, Hoffman et al., 2011; Johnson, Bradshaw, Feltovich, Jonker et al., 2011; 2014). Human-agent interdependence may come into play at various levels during joint action; for instance, it may concern task outcomes, resources, or support. As it considers human-agent interaction in the context of joint activity, Coactive Design is teamwork-oriented and thus focuses on the complementary capacities human and machine agents can contribute to the task (Bradshaw, Dignum, Jonker, & Sierhuis, 2012). The central question in Coactive Design is "how the competencies of humans and machines can be enhanced through appropriate forms of mutual interaction" (Bradshaw, Feltovich, & Johnson, 2012, p. 285). This perspective is very different from traditional system approaches (e.g., function allocation; adaptable or adaptive automation) that tend to frame the human-agent relationship in terms of supplemental capacities (Bradshaw, Hoffman, Johnson, & Woods, 2013).

The traditional position is to take a divide-and-conquer approach to system design. The emphasis is on task allocation ("what tasks can (should) the automation do, and which ones the human?") and control ("to what extent should automation be controlled by the human operator or act independently?"). Hence, intelligent systems have been conceptualized along two dimensions, self-sufficiency and self-directedness. Coactive Design adds a third dimension to system design—support for interdependence—to account for an agent's ability "to depend on others or be depended on by others" (Johnson, Bradshaw, Feltovich, Jonker, et al., 2011; p. 183). Moreover, interdependence is considered the fundamental dimension insofar as it shapes an agent's autonomy. Failure to consider the interdependency between human operators and autonomous agents results in agents that do too little and thus are a burden to the human, or in agents that act too independently from operators and thus are opaque in their actions. These relationships were confirmed in an experiment examining human-agent teamwork in a simple task environment (Johnson, Bradshaw, Feltovich, Jonker, et al., 2012). Participants who interacted with highly autonomous agents showed lower system awareness than participants collaborating with agents under low autonomy. The reverse pattern was found with respect to reported workload. Participants thought that autonomous agents reduced their workload and considered less autonomous agents as more burdensome.

Interdependent action by human and machine agents necessitates that system design not only supports their joint taskwork but also enables teamwork. Coactive Design addresses this requirement by adhering to three design principles: observability, predictability and directability. Observability means transparency and involves "making pertinent aspects of one's status, as well as one's knowledge of the team, task, and environment observable to others" (Johnson, Bradshaw, Feltovich, et al., 2014, p. 51). It facilitates teamwork behaviors, such as monitoring progress and providing backup behavior. Predictability of team members' (human and artificial) behavior makes coordinated action possible, and plays a critical role in mutual understanding. Its underlying regulatory mechanism may consist of rules or practices, as well as models. And lastly, directability refers to the capacity of team members to influence the behavior of partners, and vice versa, to be directed by them. Team members may direct others with "explicit commands such as task allocation and role assignment as well as subtler influences, such as providing guidance or suggestions or even providing salient information that is anticipated to alter behavior, such as a warning" (Johnson, Bradshaw, Feltovich, et al., 2014, p. 52).

The implementation of Coactive Design is still in its infancy. To date it has been applied extensively to the development of a humanoid robot that is able to assist a human operator during disaster relief (Johnson, Bradshaw, Feltovich et al., 2014a). While this particular implementation, as part of the DARPA Robotic Challenge, is limited both in realism and scope (it is carried out in a virtual environment), it serves to illustrate the design process and the feasibility of the overall approach. The essential component of the design process is what Johnson and colleagues call an interdependence analysis. It includes a traditional hierarchical task analysis and identifies required capacities for each subtask. In addition, it considers team members' ability to contribute (either as performer or in supporting role) to a subtask, compares alternative team role assignments, and specifies design requirements (e.g., who needs to observe what from whom) associated with role alternatives. For instance, the DARPA challenge required human-robot teams to pick up a hose and attach it to a spigot. One possible role assignment had the robot autonomously perform the grasping and lifting portion of the hose task. However, interdependence analysis determined that this solution was brittle insofar as the robot was not capable of verifying its own grasp nor could the human partner monitor the robot's action. The better—and ultimately chosen—alternative involved human-robot collaboration during which the human was able to observe and predict the robot's movement and direct it, when necessary (Johnson, Bradshaw, Hoffman, Feltovich, & Woods, 2014).

The example above also suggests that Coactive Design conceptualizes common ground between human and machine agents as an emergent property of their joint action. While proponents of Coactive Design do not dispute that team members have some knowledge in common (for instance of task objectives and rules that make their behavior predictable), they seem to consider shared knowledge as less critical to common ground than the ability of team members to observe one another, to make known to each other what their understanding is, and to be able to request and provide assistance. Johnson and colleagues (2014a) include in their Coactive System Model internal states of the human and the agent but they also point out that "the composition of the human's internal model and that of the robot are not important to the coactive system model" (p. 53) and, more importantly, that team members' knowledge need not be symmetric. On the other hand, Johnson et al. (2014a) emphasize that both human and machine agents need to be equally committed to observability, predictability and directability. However, publications on Coactive Design to date describe only how these principles are applied to the design of agents, and do not specify how reciprocity can be achieved; that is, how Coactive Design enables agents to observe, predict and direct human behavior. Future developments will show whether this lack of detail reflects task demands of the domain currently under investigation or whether it indicates technological limits in human-agent system design.

### 4.3 Related Technology: Unmanned Aerial Systems (UAS) and Robots

UAS and robot technology enable remote control of automated entities and intelligent agents, and also allow for control of more than one automated entity at a time. These human-agent teams are becoming more prevalent in domains such as aviation, space, hazardous environments, and medicine. Many of the issues mirror those of other complex automated systems, such as trust and transparency. Hancock et al. (2011) performed a meta-analysis of the factors impacting trust in human-robot interaction. Features of the robots—specifically performance and robot attributes such as robot type, personality, anthropomorphism, proximity, and adaptability—were the primary drivers of operator trust. Human-related factors such as ability, demographics, attitudes toward robots, or self-confidence were not significant factors in the development of trust, and environmental factors such as culture, task type and complexity, were only moderately associated with trust in human-robot interaction. Other human-automation interaction issues for UAS and robots include: improving and simplifying display and control interfaces; task allocation; ensuring that humans and UAS/robots have accurate mutual models of each other; avoiding unintended consequences of remote automation actions; and, as with any automated system, keeping the human operator in the loop and ready to take control if needed (Sheridan, 2016).

A critical design feature of automated entities is the function allocation scheme, which in turn suggests the LOA for the automation or robot. Kaber, Onai, and Endsley (2000) focused on the relationship between level of automation and performance using a simulation of a telerobot performing nuclear materials handling. They found that higher LOAs resulted in better performance and lower subjective workload. However, when automation failed, high LOAs had a negative impact on performance. Intermediate LOAs involving greater human control of system functions resulted in the best performance under automation failures. Adaptive allocation according to operator states and task/contextual information can potentially be used to vary LOA for optimal performance; however, the sometimes unpredictable shifting of tasks from human to automation can result in reduced SA (Kaber, Wright, & Sheik-Nainar, 2006). Kaber and colleagues investigated a double-mode cueing system to signal changes in control of a simulated telerobotic (remote-control, semi-autonomous) system. They found that bi-modal cuing (visual and auditory) of control changes was best for operator SA compared with no cues or single-mode cuing, particularly with respect to perception of elements in the environment. This finding is similar to aviation research results on multi-mode cuing (e.g., Begault & Pittman, 1996; Stanton, 1994; Wickens & Liu, 1988; Wickens, 2003), and has definite implications for information automation, as a key design issue is how to draw attention to relevant information at the right time.

Issues of transparency, trust, and accurate mental models are particularly important when automated entities are intelligent agents (IAs)—autonomous, observing the environment, acting on the environment, and performing activities to accomplish specific goals (Russell & Norvig, 2009; Mercado et al., 2016). Unless human operators understand the rationale underlying IA actions, they will be less likely to use the IA, and its ability to support SA and performance will be limited (Chen & Barnes, 2014; Lee & See, 2004; Linegang et al., 2006). However, some research has proposed that there is a trade-off between transparency and response time and workload, such that the additional information processing induced by increased transparency increases both response time and workload (e.g., Dorneich et al., 2015; Letsu-Dake et al., 2015), suggesting that level of transparency or feedback may need to vary as a function of contextual factors, such as the presence of an emergency condition. Mercado et al. (2016) investigated the impact of transparency on performance, trust, workload, and usability. Participants used an IA to select the 'best plan' for unmanned vehicle mission assignments under three levels of transparency: 1) basic plan information; 2) basic plan information + IA reasoning and rationale; or 3) basic plan information + IA reasoning and rationale + projection of uncertainty information and how it would impact a successful action. In contrast to Dorneich et al. and Letsu-Dake et al., results showed benefits in terms of operator performance, trust, and usability with increases in transparency level—with no costs in terms of response time or workload. More research is needed, particularly in realistic tasking environments, to clarify the relationship between transparency and performance variables.

To address the issue of multiple-entity management, Fern and Shively (2009) conducted a simulation of multiple unmanned aerial systems (UAS) and compared Playbook (multiple UAS automation) against manual control (no automation) and scripts (single UAS automation). When in the Playbook mode, participants could select a play that would control three UAS at once, and could execute behaviors such as setting automatic flight paths or firing weapons. Plays showed a distinct advantage over manual control or scripts, in terms of both performance and workload. A follow-up study demonstrated that the Playbook interface was robust enough to handle "non-optimal play environment" (NOPE) events, that is, events for which higher levels of delegation were not optimal and some reversion to manual control was required (Shaw et al., 2010). Further, several studies investigated whether use of Playbook over time would produce complacency and automation bias, resulting in difficulties in performance when reverting to lower levels of delegation or manual performance. In the playbook condition, researchers focused on performance in NOPEs: 'pop-up' targets that appeared outside of normal operations and required manual UAV control to locate. Rather than finding that use of plays promoted complacency and loss of familiarity with manual tools, they found that having plays available during most of the trial helped participants perform better during the NOPEs (Miller et al., 2011; Shively, Flaherty, Miller, Fern, & Nieswander, 2012). The researchers posited that "having well-fitting plays during other portions of the trial may have freed up enough mental 'bandwidth' and situation awareness capacity to allow users to 'stay ahead' of the situation and better deal with the NOPE when it occurred" (Miller et al, 2011, p. 98). A second experiment with longer trials, however, found conflicting evidence in that NOPEs early in the trial disrupted performance for the playbook condition more than for the manual tools condition. By the second NOPE, however, the disruption evened out across conditions. Researchers suggested that overreliance on Playbook decreased over time, again supporting the position that Playbook does not induce complacency (Shively et al., 2012).

Playbook also showed promise for UAS control to support both manned and unmanned teaming from the cockpit of a helicopter. Using a simulated low-level terrain flight mission, Shively, Neiswander, and Fern (2011) compared performance of six participants in three conditions of UAS control: no UAS, UAS with manual control, UAS with Playbook control. Playbook automation enhanced primary task performance and lowered overall workload, demonstrating the effectiveness of the approach for control of multiple UAS from the cockpit. Of particular interest were the results for UAS route replanning performance. Playbook was able to use a 'Wingman play,' in which "…the UAS was tethered to the ownship, such that the route and groundspeed were automatically matched" (p. 3). This negated the need to input updates to the UAS flight plan, and resulted in significantly less time for route changes compared with the manual control mode.

Much of the research on UAS and robots with respect to system design echoes the findings from aviation work in information automation discussed above: 1) attention-getting features are critical; 2) transparency is important for trust and so that the human operator can develop an accurate mental model of the automated system; 3) displays and interfaces need to be as simple and uncluttered as possible; and 4) keeping the human operator in the loop is essential. Higher LOAs benefit performance and workload in nominal situations but may hinder SA as well as recovery when automation fails. Additionally, findings with respect to the impact of robot personality and anthromorphism suggest that context-sensitive information management systems may benefit from adopting characteristics that emulate humans (such as human-sounding voices for auditory information or interaction conventions typical in human-human interactions such as politeness or acknowledgements).

### 4.4 Lessons Learned from Existing Information Automation Systems

All of the decision-support systems discussed above provide a degree of enhanced information management and decision-making capabilities for the pilot. The newest models of information management and decision support can be tapped for effective design and implementation of context-sensitive information automation. A notable facet of these systems is that they are designed to function as much as possible, given the capabilities of current technology, like a human team member, and to exhibit desirable human-like characteristics such as transparency and observability of actions, predictability of next actions, and responsiveness to direction. They are also expected to take on many functions that we would traditionally associate with the Pilot Monitoring: attending to and if necessary challenging the actions of the pilot flying and backing him/her up, synthesizing and feeding information, taking over tasks as needed to reduce pilot workload, and assisting with situation assessment and decision making. To some extent they are expected to 'sense' what information is needed at a given time, and when the human team member is too overloaded to absorb additional information.

Research on these systems also suggests new capabilities that should be integrated into context-sensitive information automation. For example, existing systems stop short of functioning as a true automated team member as described in the following sections on team effectiveness, and none possesses the ability to self-adapt to changing situations, to inform the pilot when information is no longer timely or is limited in scope (i.e., what the automation does not know), to sense and change behavior according to environmental conditions such as turbulence, or to integrate airline policies and regulations that are not pre-programmed as limitations (e.g., they do not inform the pilot to slow to 250K below 10,000', or to discontinue an approach if not stabilized). Moreover, current systems cannot sense human states such as fatigue or stress and tailor their functioning to these states. They cannot evaluate the accuracy of pilot situation (mental) models, independently suppress information when it is not relevant, push information to facilitate the development of accurate mental models, or contribute proactively to the human-automation team. Because of these limitations, current information automation is still to a great extent 'brittle,' may sometimes hinder rather than facilitate pilot SA and decision making, and cannot function as a truly effective human-automation team member.

Components of successful human-automation teams mirror those of effective human-human teams; thus it is critical for the design of context-sensitive information automation to specify and emulate the factors that enable effective human-human teams.

## 5. Human-Human Teams: Components of Team Effectiveness

'Teamwork' has been a central issue in the training of commercial pilots since the late 1970s when accident investigators identified shortcomings in pilots' non-technical skills, such as leadership and followership, crew communication and coordination, as causal factors in airplane accidents and incidents (Helmreich, Merritt, & Wilhelm, 1999). These accidents brought to the fore the acknowledgment that technical expertise of pilots alone is not sufficient to ensure flight safety; in addition, pilots need to act as a team.

A team is commonly defined as a group of at least two individuals who are brought together to work on a common cause. Team members have distinct roles and responsibilities and need to work interdependently to meet task objectives. Members' interdependence concerns their workflow, goals, and outcomes (Harris & Beyerlein, 2003; Koslowski & Ilgen, 2006; Salas, Guthrie, Wilson-Donelly, et al., 2005; Stewart & Barrick, 2000). However, merely bringing together individuals with task-specific expertise is not sufficient to ensure effective task performance. What is needed instead is that individuals function as an integrated and interdependent unit (Salas, Cannon-Bowers, & Johnston, 1997). Much research on teamwork has been devoted to understanding critical team processes—communication, coordination, and cooperation—and their constituent competencies: shared mental models, mutual performance monitoring, backup behavior, adaptability, leadership, team orientation, and mutual trust (Salas, Sims, & Burke, 2005; Salas, Shuffler, DiazGranados, 2010; Wilson, Salas, Priest, & Andrews, 2007).

## 5.1 Team Communication

Teamwork requires communication. While this statement sounds almost banal, its realization is anything but simple. Failures in team communication are frequently identified as factors in accidents and incidents in aviation (Sexton & Helmreich, 2004), healthcare (Leonard, Graham, & Bonacum, 2004; Reader, Flin, & Cuthbertson, 2008), off-shore oil drilling operations (Flin, O'Connor, & Crichton, 2008), or nuclear power plants (Fukuda & Sträter, 2004). Whether team members are inches apart or hundreds of miles distant, they need to share critical information to ensure common ground concerning their task, teamwork, and the evolving situation. Communication enables team members to provide critical feedback and support, and to coordinate adaptive responses to changing task conditions.

Participants in face-to-face interactions can usually assume that information in their common visual field is mutually known. Likewise, pilots may presume that whatever is visible on displays and in the external environment, or is audible to both of them, is information shared. However, this belief can be misguided as data and information may allow multiple interpretations and pilots may come to a different understanding of the same input (Fischer, Orasanu, & Davison, 2003). Additionally, communication occurs concurrently with other tasks, and crewmembers may be preoccupied with different demands. Therefore specific steps need to be taken to facilitate crew communication and support common ground between pilots. The challenge is to correctly judge what information teammates need, when to communicate it, and how to communicate efficiently.

### 5.1.1 Challenge 1: What Information to Convey

Communication procedures prescribe the exchange of specific information at particular points during a flight. These so-called Standard Operational Procedures (SOPs) include specific callouts that crewmembers are required to make, for instance to announce when a pre-specified altitude has been reached. SOPs also refer to checklists that detail crew actions in response to routine or abnormal events. During normal operations, one crewmember—typically the pilot monitoring—reads aloud the checklist and the pilot flying acknowledges each item. The sequential structure of checklists not only guides crewmembers through oftentimes complex tasks but also ensures that they have a shared situation understanding.

However, not all pilot communication is covered by SOPs. Pilots work in a dynamic task environment where changing conditions require that they reassess their original plan and respond adaptively to evolving events. Non-SOP talk goes beyond the exchange of routine information and concerns flight safety-related events and pilots' problem solving efforts (Orasanu & Fischer, 1992). Effective communication in these situations addresses critical components of a crew's task and teamwork and promotes shared situation models. Effective crews have been found to talk more about the problem they faced and their response to it than did poorly performing crews (Bourgeon, Valot, & Navarro, 2013; Helmreich & Foushee, 2010; Mjos, 2001; Sexton & Helmreich, 2000). In particular, successful teams are more likely to articulate new plans and changes in task allocation as well as state expectations about future events and provide status updates (Gillan, 2003; Orasanu & Fischer, 1992).

Members of successful crews are also more explicit about their reasoning. For instance, Bourgeon and colleagues (Bourgeon et al., 2013) observed that crews who discussed critical aspects of their current flight situation and justified their opinions based on available information, were also less likely to commit continuation errors; that is, to stick to a plan of action even in the face of information inconsistent with their decision. Cognitive transparency, moreover, not only promotes deliberate decision making but is also associated with effective threat and error management. As shown by Fischer and her collaborators (Fischer & Orasanu, 2000; Fischer, Rinehart, & Orasanu, 2001), crewmembers can mitigate pilot error most effectively by using communication strategies that state what action the crew—as opposed to the individual pilot—is to take, and in addition provide a justification for the action request, such as when a problem is identified or how a requested action will achieve an agreed-upon goal. Both captains and first officers rated action requests that were supported by a reason as more effective than directives without supporting statements, presumably because the supporting statements enabled crewmembers to verify the accuracy of their situation understanding and contributed to a shared situation model.

### 5.1.2 Challenge 2: When to Provide Information

SOPs, in particular those that concern routine operations, not only prescribe what has to be communicated but also frequently indicate when the communication has to occur. The timing specification is thus part of a given communication procedure; for instance, altitude callouts during the landing phase. In the absence of SOPs, crewmembers need to decide when it is appropriate to talk. During face-to-face interactions, team members tend to be mindful of each other's workload and time their communication so as to avoid disrupting ongoing tasks. Effective team members are also able to anticipate the information their teammates need and provide it to them rather than waiting for them to request it. Such anticipatory information sharing has been associated with successful team performance (Butchibabu, Sparano-Huiban, Sonenberg, & Shah, 2016; Entin & Serfaty, 1999; MacMillan, Entin, & Serfaty, 2004). The timing of communication is also an important consideration during performance monitoring. When critical events arise, such as a system malfunction or an unsafe action by a colleague, pilots' interventions depend on their assessment of the severity and time criticality inherent in the situation (Fischer & Orasanu, 2000). Moreover, position of authority plays a role in the timing of interventions. In high risk situations captains were found to call for a corrective action as soon as they perceived conditions to be deteriorating. In contrast, first officers were less likely to intervene preemptively (Orasanu, Fischer, McDonnell, Davison, et al., 1998)—a behavior which ultimately could lead to poor error management.

### 5.1.3 Challenge 3: How to Communicate Efficiently

SOPs also contribute to communication efficiency. Standard terminology, prescribed callouts, and checklists enable pilots to come to a shared understanding of their flight situation at relatively low cognitive costs. SOPs are part of pilots' task knowledge and thus require little cognitive effort to produce and to comprehend.

During interactions that are not governed by SOPs, crewmembers communicate efficiently by structuring their contributions in closed loops. That is, they immediately let others know that they heard and understood their contributions; for instance, questions are answered right away, and observations acknowledged or elaborated upon. Read-backs or contributions that build or elaborate on the preceding utterance are strategies by which pilots can indicate understanding of what was said (Fischer, McDonnell, & Orasanu, 2007). By engaging in 'closed-loop' communication crewmembers are able to establish mutual understanding without unduly increasing their cognitive load. Moreover, because thematically related contributions follow one another in a coherent fashion, conversations have a tight structure and comprehension problems are quickly detected and repaired. Adherence to closed-loop communication is common in high-performing flight deck crews whereas deviations from normative patterns are prevalent in crews involved in aircraft accidents and incidents (Dietrich, 2004; Kanki, Lozito, & Foushee, 1989).

## 5.2 Team Coordination

Teamwork also requires that team members coordinate their individual actions. Team coordination, in turn, is facilitated by shared mental models and involves specific behaviors: performance monitoring, backup behavior, adaptability, and leadership.

### 5.2.1 Shared Mental Models

Shared mental models refer to common or compatible mental structures that represent team members' task- and team-related knowledge (Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000; Stout, Cannon-Bowers, Salas, & Milanovich, 1999). For pilots these models comprise detailed knowledge of flight deck systems and flight operations, as well as an understanding of their flight plan and of their current situation, and they include knowledge relevant to teamwork, such as their individual roles and responsibilities and how they, as a team, are to interact (Orasanu, 2010). Some aspects of this knowledge are part of pilots' common ground by virtue of their shared expertise and training; it is knowledge that pilots bring to the task. Pilots' knowledge is also adaptive, shaped and created by shared experience and through communication. Shared mental models are an essential coordinating mechanism in teamwork. They provide pilots with an interpretive framework for their joint actions, aid communication efficiency, and are a prerequisite for mutual performance monitoring and backup behavior.

### 5.2.2 Mutual Performance Monitoring

Coordinated action by team members depends on mutual performance monitoring. Team members need to know what others are doing and if necessary, adjust their own behavior. Mutual performance monitoring is also an essential element of threat and error management. In addition to performing their individual tasks, crewmembers need to monitor each other's performance and need to intervene if a problem is detected to prevent a situation from deteriorating. Failure to do so may have severe consequences. Inadequate monitoring by crewmembers has been implicated in many aviation accidents (NTSB, 1994) and incidents (Mosier, Fischer, Cunningham, Munc, et al., 2012; Sumwalt, Thomas, & Dismukes, 2003).

Two prerequisites of effective performance monitoring have been suggested (Marks & Panzer, 2004; Salas, Cooke, & Rosen, 2008). The first one is shared mental models. Team members need to have a common understanding of their task and current situation, and they need to agree on their assigned responsibilities, including a shared belief in the importance of performance monitoring. Incompatible task or team models render performance monitoring meaningless or ineffective. A second prerequisite is mutual trust. Team members need to trust that others monitor their performance because it is the accepted norm and not because one simply wants to be critical of the other. The move by airlines to rename the non-flying pilot as the pilot monitoring reflects this consideration. The designation ‘pilot monitoring’ establishes behavioral standards and by mandating that any pilot must abide by them, takes away the negative connotation of performance monitoring.

### 5.2.3 Backup Behavior

Both performance monitoring and backup behavior are metacognitive in nature. Team members self-assess how they, as a team, are performing and whether some intervention is necessary to maintain performance standards. Types of backup behavior are: providing feedback and coaching to improve task performance; assisting a teammate in carrying out a task; and assuming and completing a task for a teammate when he/she seems overextended (Marks, Mathieu, & Zaccaro, 2001). Necessary antecedents to backup behavior are accurate performance monitoring as well as task and team models insofar as they form the basis on which team members determine who needs support and how best to provide it. Backup behavior also includes requests for assistance. In effective teams, members are expected to let others know when task demands exceed their capabilities (Wilson et al., 2007). In addition, effective backup behavior requires that teammates have the expertise necessary to provide assistance, and that others are willing to accept help (Smith-Jentsch, Kraiger, Cannon-Bowers, & Salas, 2009). For instance, Orasanu and Fischer (1992) analyzed pilots’ interactions during simulated off-nominal flight events and found that first officers in poorly performing crews suggested more plans and strategies than their counterparts in successful crews, apparently in an effort to compensate for the lack of leadership by captains. Unfortunately, their efforts were not always successful as captains did not respond to their suggestions or dismissed them outright.

Backup behavior is also associated with team adaptability. The ability of team members to identify performance weaknesses and to mitigate them by redistributing their efforts affords them with the flexibility necessary to respond to shifting task conditions. As Salas and colleagues (2005) note “the importance of backup behavior does not simply lie in improved performance outcomes but rather in how backup behavior affects team processes to allow greater adaptability in changing situations and environments” (p. 579).

### 5.2.4 Team Adaptability

Flight deck crews work in dynamically changing operational conditions and as a result need to adjust their behavior accordingly to maintain flight safety. Adaptability involves crewmembers monitoring aircraft systems and the external environment for cues suggesting that their current actions or plans are no longer adequate and that they need to modify their approach. Such decisions can be challenging since ongoing tasks and established plans tend to be “sticky” and thus hard to dismiss (Wickens, Santamaria & Sebok, 2013), especially if a shift comes with costs (e.g., missed flight connections by passengers). Plan continuation errors—that is, the decision by flight crews to continue with an original course of action in the face of cues that signal changed conditions—is a well-documented phenomenon both in aviation accidents (Orasanu, Martin, & Davison, 2001) and incidents (Orasanu, Burian, & Hitt, 2001).

Team adaptability requires that team members maintain an accurate situation model. It also requires a trusting and open team climate in addition to effective team communication (Burke, Stagl, Salas, Pierce, & Kendall, 2006). Team members need to feel assured that they can express concerns about their team’s performance and are able to propose alternatives. Effective team communication is critical to ensure that team members come to a shared situation understanding and adjust their task and team models to ensure coordinated action.

### 5.2.5 Team Leadership

Team leaders play a pivotal role in team coordination although the nature of leadership may vary. Leadership may be shared among team members or emerge during joint work. Flight deck crews are characterized by a hierarchical team structure with the captain as the leader who orchestrates the teamwork, especially in response to off-nominal and emergency events. Effective captains structure the crew's response to a problem (Orasanu & Fischer, 1992). They explicitly state their plans and explicitly allocate tasks among crewmembers. By stating their plans, they let other crewmembers know what they want to accomplish. This allows other crewmembers to offer contributions and take actions that are consistent with the captain's intentions. It also creates a context within which the captain's orders or information requests can be interpreted. Effective captains also include subordinates in the decision making process, and encourage them to voice concerns and disagreement, and to assert their positions (Helmreich & Foushee, 2010).

## 5.3 Cooperation

Team members' communication and coordination are driven by a shared commitment to cooperation. If team members were not willing to cooperate, their communication would be dysfunctional or non-existent and likewise, their attempts at coordination. Team members' commitment to cooperation is based on two core beliefs and attitudes: team orientation and mutual trust.

### 5.3.1 Team Orientation

As an attitude, team orientation is defined as the "[p]ropensity to take other's behavior into account during group interaction and the belief in the importance of team goal's over individual members' goals" (Salas et al. 2005. p. 561). On the behavioral level, team orientation means that members are cooperative and volunteer information; they inquire about and take into account the perspective of others, show regard for their contributions (Goodwin, O'Shea, Driskell, & Ardison, 2004). Team orientation is also closely related to trust.

### 5.3.2 Mutual Trust

Team orientation entails trust in one's teammates (Goodwin et al., 2004). Moreover, 'trust' as a team-level variable is reciprocal: members are confident that teammates will play their part competently, pursue common goals and will not hurt them. As a result, team members are inclined to share information and resources, and are willing to provide and accept performance feedback and assistance (Salas et al., 2005). The extent to which team members trust each other also influences how they will interpret teammates' actions—for instance, whether they will perceive a teammate's offer of assistance as cooperative or patronizing; or performance monitoring as an effective strategy to mitigate errors or as a threat.

Team orientation and mutual trust reflect individual traits but both are also shaped by experience (Yakovleva, Reilly, & Werko, 2010). As team members work together they have the opportunity to judge how trustworthy others are, and whether they are team players: Are they reliable and responsible? Are they contributing to the team's goals? Are they working with others? Are they supporting their teammates? Organizations and team leaders can facilitate the development of team orientation and mutual trust within a team by setting and reinforcing behavioral standards that promote cooperative attitudes (Salas et al., 2005).

## 5.4 Implications for Human-Automation/Autonomy Teaming

As flight deck automation is becoming more capable, it seems natural to view it as a member of the crew (Christoffersen & Woods, 2002; Prinzel, 2003) and to talk about human-automation teaming. In contrast, some (e.g., Pritchett, 2009) have argued that the notion of automation as a team member is ill-conceived because automation lacks affective and cognitive processes comparable to a human. This position, however, seems to apply an unnecessarily high standard; instead it may be sufficient to expect that automation can function as a team member insofar as it can engage in behaviors and has knowledge critical to teamwork. Adopting this level of comparison allows us to draw on research findings on the effectiveness of human teams to define parameters for design of flight deck automation.

### 5.4.1 Teamwork Involves Interdependent Agents

One fundamental issue the discussion of human-automation teaming needs to address is the nature and degree of the interdependence in a human-machine team. Insofar as a (human) team is defined as a group of interdependent agents with specified roles and responsibilities, the same should hold in a team involving human operators and automation. Specifically, human-automation interdependence implies:

- Task performance in the context of human-automation teaming requires the *collaboration* of pilots and automation and the *integration* of skills and knowledge or information that each of them contributes.
- Pilots and automation have *complementary responsibilities*; however, as dictated by team adaptability, responsibilities may be reassigned to meet changing task demands.

### 5.4.2 Human-Automation/Autonomy Interaction (HAI) as Team Communication

Human-automation teaming also requires human-machine interactions that go beyond pilots programming automation or hitting a start button. Instead HAI has to be comparable to communication in human teams pertaining to content (what information needs to be shared?), timing (when to communicate?), and efficiency.

As with pilot communication, HAI may be regulated by SOPs that prescribe the content and timing of team communication. However, SOPs—at least in their current format—are tied to specific events. Crew communication, in contrast, is not limited to SOPs but shows greater flexibility. Effective crewmembers are adept communicators even in the absence of SOPs. They know what information to communicate when, and are efficient in doing so. Effective team members tailor their communication to the knowledge and information needs of teammates and to situational demands. They can do so because they can "read" their teammates. They know what others know, and because they interact face-to-face, they see what others are doing, where they are looking, and what escapes their attention. Crewmembers' ability to communicate effectively is grounded in shared task and team models, as well as common situation models. The challenge for system designers is how to incorporate the notion of such shared knowledge into HAI.

Team communication, however, is not simply a matter of pushing information; rather it also involves information sharing. This issue comes to fore when crewmembers need to respond to changing operational conditions. In these situations, members of high-performing crews address the significance of cues, discuss their options and explain their reasoning. That is, team members create a shared situation model as they communicate. Likewise, HAI as part of human-automation teaming needs to support information sharing so that pilots, at a minimum, can pull information from the automation as well as provide information (e.g., observations, considerations) to the automation for evaluation, and vice versa, that automation can request and give information. This type of HAI may in future require speech-based communication (via voice synthesizer and speech recognition) between pilots and automation.

### 5.4.3 Shared Mental Models

A prerequisite of effective team performance is that team members have compatible models of their task, teamwork and operational environment. Common ground between crewmembers involves knowledge they share because of their professional training, educational and cultural background; it also involves knowledge added as they work together. Approaches to common ground between pilots and automation fall into two camps, conceptualizing it either as stock of common knowledge or as information sharing. Proponents of the first approach may focus on the system knowledge of pilots (i.e., pilots need to know what and how automation knows), or conversely, on the user model built into the system (i.e., knowledge that automation needs to have to support inferences about a pilot's intentions and situation awareness; Miller & Hannen, 1999), or lastly, they may emphasize the compatibility of system characteristics with a pilot's task model and control strategies (Kaber, Riley, Tan, & Endsley, 2001). Proponents of the information sharing approach to common ground may target system transparency—i.e., the system should clearly indicate (communicate explicitly) its current state, goals, knowledge, hypotheses and intentions (Woods, Roth, & Bennett, 1990)—or they may stress the collaborative nature of communication (Miller, 2004); that is, pilots would be required to explicitly accept information or directives as understood, and conversely pilots' input to automated systems would have to be explicitly acknowledged by the system. Requiring pilots and systems to provide evidence of their understanding may be especially important when automation presents critical information or when pilots propose significant changes to the system status.

### 5.4.4 Mutual Performance Monitoring

Automation should be able to flag pilot input that is inconsistent with previous inputs, system states, plans or goals, and suggest or implement alternative(s) dependent on criticality of event (Marstall, Miller, & Poisson, 2016). Moreover, automation should provide an explanation for its intervention, either by volunteering it or when the pilot requests it. Because performance monitoring is reciprocal, pilots also need to be able to monitor the system for irregularities and errors. This requirement calls for automation that conveys, at a minimum, its status, ongoing activities, and goals, and is able to provide additional explanations upon pilot request.

### 5.4.5 Backup Behavior

Ideally backup behavior in human-automation teaming should mimic interventions in human teams. That is, pilots should be able to request assistance, and automation should be able to offer assistance. Pilots should be able to adapt the level of assistance provided by automation to their workload, and conversely, automation should be able to infer a pilot's workload and suggest changing its level of assistance accordingly. The latter behavior requires that automation is able to identify significant changes in a pilot's workload either derived from context information, such as phase of flight or number of tasks to be completed, or based on behavioral or physiological measures.

The analogy to human teams should also pertain to the types of backup behavior available to human operators and automation. Usually joint work by human operators and automation is framed as division of labor; that is, tasks or subtasks are performed either by the human or by the automation. Backup behavior in human teams, in contrast, includes collaboration in which tasks are performed jointly by team members. Likewise, automation should be able to provide feedback or coaching to a human operator, or support him/her during task performance.

#### 5.4.6 Team Adaptability

The ability to respond adaptively to changing task and environmental conditions is critical to any teamwork, so too in the context of human-automation teaming. A recurrent finding is that team members fail—or are too slow—to recognize that they need to adjust their behavior. In contrast, decisions on what changes to make and how to implement them are rarely the major problem. Pilots' plan continuation errors are examples of poor adaptability by human teams due to the crewmembers' faulty situation awareness. In HAI this phenomenon is known as decompensation (Branlat & Woods, 2010; Woods & Cook, 2006); in other words, the human operator fails to detect that the automation is working at its limits to compensate for changed conditions, and intervenes too late. Examples from aviation include cases of asymmetric lift due to icing or slowly building engine trouble where "automation can silently compensate but only up to a point. Flight crews may recognise and intervene only when the automation is nearly out of capacity to respond and when the disturbances have grown much more severe" (Woods & Branlat, 2011; p.131). These instances also illustrate that adaptive responses by human-machine teams require team communication and a shared understanding of their situation, task, and teamwork. Pilots were late in recognizing a problem because the automation could not, and thus, did not let them know that it was working near capacity, nor could pilots tell that this was the case.

#### 5.4.7 Team Leadership

As in human teams, human-automation teaming requires clear leadership. Because pilots are ultimately responsible for decisions taken by the human-machine team, they need to have the flexibility to orchestrate human-machine teamwork dependent on situational demands and their workload. However, there needs to be the possibility for automation to "speak up" in situations in which it judges pilot actions to pose a serious safety threat. Likewise, automation should be able to push information that it deems critical to pilots' decisions, and to offer assistance if it senses pilot overload. That is, automation should be able to fulfill the critical monitoring and error mitigating functions that are mandatory for crew resource management.

#### 5.4.8 Team Orientation and Mutual Trust

Interdependence of human operators and automation requires that team orientation and trust characterize both human and machine agents. For the human operator, team orientation plays out as trust in the automation while trust is based on system features, such as reliability and transparency. For the automation, team orientation and trust are design features. The former may be achieved, for instance, by making automation transparent concerning its current state, goals, etc. or by enabling it to push information (Woods, et. al., 1990). The system's trust in the human operator is manifest in the extent to which it supports (or constrains) operator control over system functions.

## 6. Conclusion

In this document we have explored a great number of issues associated with the development, design, and functionality of autonomous, context-sensitive task management and decision support tools. The amount of information automation available in many work domains, including aviation, is prolific and increasing daily. The development of effective autonomous systems and tools to help collect, sort, integrate, and interpret this vast trove of information is critical lest human operators become buried by it or paralyzed from taking meaningful or timely action based on it. Development may require a constellation of linked or integrated systems or tools rather than just a single one (Durfee, 2016).

As long as humans are involved in the work, it is critical that even the most autonomous of information management systems behave as members of a team, fully supporting their human counterparts. These systems must also be context-sensitive and robust, seamlessly adapting what is offered and when to conditions and situations, as they are encountered, and the workload and functioning of their human partners.

The desired characteristics of such an automation information management team member are listed below as 'First Principles.' In philosophy, mathematics, physics, and other fields, first principles are basic, foundational, or core propositions or assumptions that are considered self-evident. We propose the following first principles for human-automation/autonomy teaming in keeping with this perspective:

1. Automation/Autonomous System (AAS) is a team member.
2. AAS completes tasks autonomously, jointly with the human, or not at all.
3. Humans have decision authority; that is, the human authorizes decisions/ actions recommended by AAS; however,
4. AAS provides a fail-safe to prevent unsafe actions by the human.
5. Tasks can be distributed across human and AAS in real time as needed.
6. AAS is transparent, which makes feedback/clear information available to the human with regard to:
   a. Its "understanding" of a situation, or the task/plan to be accomplished.
   b. What tasks it is completing (task execution).
   c. Assumptions it has made with regard to how it is completing those tasks, if pertinent.
   d. The information sources and the rationale behind decision/action recommendations.
7. AAS is cognizant of human workload and assists in its management; AAS does not increase human workload.
8. AAS pushes information in a timely fashion while taking into account human workload, time constraints, and the safety/criticality of a situation.
9. AAS monitors human actions and identifies human errors or suboptimal decisions.
10. Interactions between the human and AAS are accomplished in a variety of modes (visual, voice, aural, haptic) so that no sensory mode is overloaded.

Readers may recognize that at their core, most of these first principles pertain to fundamental values underlying human social and ethical behavior. At the highest level the values reflect: 1) respect for autonomy/human dignity; 2) beneficence;3) non-maleficence; and 4) justice (Bond, 2015; Stone & Veloso, 1997).

The first norm, respect for autonomy/human dignity, pertains to respecting the autonomy and primacy of the human in human-automation teams. As discussed earlier in this report, automation and autonomous systems should be reliable, predictable, and transparent in their behavior. Humans should not be left guessing as to what the system is doing or what it will do next (Sarter, Woods, & Billings, 1997). Inevitably there may be cases in which the automated system is specifically designed to take over or be in charge (Endsley & Kaber, 1999; Sheridan, 1992). To facilitate cooperation in these instances, AAS should be expected to explain why it has taken over and when control will be returned to the human.

The principle of beneficence requires that automation and autonomous systems are designed to benefit and further the goals of their human partners. Humans who work together on teams demonstrate beneficence by sharing information and coordinating actions to achieve shared goals. System designers must ensure integrity of information automation and autonomous systems in that the systems provide or make available accurate information that is needed, when it is needed, while taking into account human and situational constraints and demands. When automation commits errors, such as providing faulty advice, "apologizing" for having done so and working to remedy the situation may facilitate trust resilience (de Visser et al., 2016).

Automated systems also should be designed so that their limitations and failures cause as little harm to the human-automation team as possible, as prescribed by the principle of non-maleficence. In human-to-human interaction intentionally causing harm is avoided; should harm occur, the one causing the harm takes responsibility to ameliorate it to the degree possible and make amends to counter its effects. Automation and autonomous systems can be designed to incorporate non-maleficence in a number of ways. For example, when they degrade they should do so transparently and "gracefully" rather than "cutting and running" and "dumping everything in the human's lap" to sort out (NTSB, 1996). Similarly, information automation should help to keep humans from taking action based on information that may not be accurate by informing human partners of limitations to the information presented: how "sure" is it that the information it is sharing is valid and reliable? Non-maleficence may be one of the most difficult principles to design into information automation and autonomous systems. Currently, automation may appear to "know what it is doing," but it lacks insight and has no metacognitive ability to evaluate what it thinks it "knows" or the assumptions upon which its suggestions are based. Work in artificial intelligence has made some progress in this area but has not yet achieved this milestone (Arroyo et al., 2014).

The final principle of justice pertains to equitable treatment and fairness. In human interactions, justice means that all humans are treated equitably and fairly and that both benefits and obligations are shared. Implementation of these norms has not yet been accomplished with respect to automated systems. Despite cutting-edge programming, advanced machine learning, fuzzy logic, and sophisticated algorithms, autonomous systems and tools will still likely be vulnerable to error. The precise vulnerabilities are likely to be unexpected resulting from a combination of unpredicted conditions. The issue of responsibility for errors is complex and is likely to evolve as automated systems function more autonomously. From a justice perspective, it is reasonable to posit that responsibility for errors should not just fall on the human team member alone, but instead should be shared among the entire system, including the autonomous system and developers of the automation.

It may seem peculiar to apply social and ethical principles for human behavior to the design of automation and autonomous systems (Durfee, 1992). After all, in aviation and many work domains we consider these systems to be tools, assistants, or even "team members," but we do not expect them to think ethically. Moreover, we do not even expect them to have the same sort of personal proximity or relationship to humans as next generation social robots who provide caregiving or nursing might have (Veruggio, Solis, & Van der Loos, 2011). Nonetheless, research on human conceptions of interaction with, and trust in, automation and autonomous systems (Lee & See, 2004; Hoff & Bashir, 2015; Turkle, 2005) —particularly systems with anthropomorphic features and behavior (de Visser et al., 2016; Pak et al., 2012)—indicates that human expectations are changing as automation evolves and that such an application is appropriate. Adopting the perspective that automation should be designed to reflect human social and ethical norms may be imperative as automation behaves more autonomously.

Autonomous, context-sensitive, task management and decision support information automation holds great promise for the information rich and high workload domain of aviation. However, this is only true to the degree to which these systems behave appropriately as dictated by human social and ethical norms, are designed well according to established HAI principles, and reliably provide the exact right information and decision support when needed.

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