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Reducing Human/Pilot Errors in Aviation Using Augmented Cognition and Automation Systems in Aircraft Cockpit

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Abstract:

Human errors cause the majority of aviation accidents. Augmented cognition and automation systems enhance pilot performance by evaluating system limitations and flight precision and performance. This study examines the human-machine interface in cockpit design using the tenets of augmented cognition and automation systems theory in terms of task allocation, attentional resources, and situational awareness. The study compares how these principles apply to and interact with each other and with a human/pilot in a closed-loop system. We present a method for integrating augmented cognition systems into airplane flight management systems. We demonstrate systems enhancement with an experiment in which test pilots flew two simulated flights, once without and once with an augmented cognition system. We measured pilot and airplane performance, pilots' situational awareness, workload management, pilots' use of cockpit checklists, and flight precision along four axes: (1) altitude, (2) course, (3) radial/bearing and heading, and (4) airspeed.

Keywords: Augmented Cognition, Automation in Aviation, Aviation Accidents, Aviation Safety, Avionic Technology, Cockpit Design, Human Factors in Aviation, Human-Machine Integration, Pilot Error, Situational Awareness, Systems Engineering, Work Prioritization, Workload Saturation.

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1 Introduction

Approximately 80 percent of all aviation accidents are related to human—primarily pilot—errors, and the majority of these accidents occur during landing (24.1 percent) and takeoff (23.4 percent) (National Transportation Safety Board, 2014; Federal Aviation Administration, 2012). Advancements in aviation technology have led to the development of complex cockpit systems that have highly interrelated components. Although this advancement has significantly increased efficiency and resulted in the development and operation of enhanced systems such as cockpit automation, it has also meant greater work overload and posed the danger of system-induced catastrophes. Numerous studies show that, to some degree, cockpit automation poses the danger of disengaging the pilot from the cockpit. With technological advances in avionics, automation, and computing processes, the trend seems to be disengaging pilots from their work (Casner & Schooler, 2014; Norman & Orlady, 1988; Casner, 2009). This trend influences pilots' situational awareness and their aeronautical decision making (ADM). Therefore, we need to understand how humans make decisions and how pilots can improve their ADM skills. This study demonstrates that this can be accomplished through using an augmented cognition system (ACS) in the cockpit by improving the human-machine interface through the human-in-the-loop concept. An understanding of augmented cognition systems illustrates how workload and task prioritization can influence decision making and how those factors can be modified to enhance safety in the flight deck. It also keeps the pilot engaged with flight systems in all phases of the flight.

So far, many studies concerning automation have been performed. Casner and Schooler (2014) demonstrate that using more automation allows pilots to engage in fewer tasks-at-hand and focus more on higher-level tasks. At the same time, when more automation is used, measures of pilot awareness show that less, not more, higher-level flight-related thinking has occurred. Norman and Orlady (1988) argue that cockpit automation allows pilots to devote more time to monitor the health of the airplane, plan around potential weather hazards, respond to air traffic controller, and plan for alternatives should anything go wrong. But Canser and Schooler (2014) question how pilots make use of this free time.

Several studies including the one by Canser (2009) have confirmed that, at least during some phases of flight, automation can certainly help lower pilot workload and free up time. But, contradictory to these hopes, other work shows that pilots flying under high levels of automation are not using their free time to monitor the health of the airplane, plan around potential weather hazards, or plan for alternatives if something goes wrong. Endsley and Kiris (1995) show in several experiments that, when pilot awareness was assessed, pilots could not answer basic questions about their situation. Canser (2005), by showing that pilots did not know where they were, reaches the same conclusion.

Roscoe (1992) claims that increases in cockpit automation have resulted in changing the pilot's role to more of a manager or supervisor than an active controller of an airplane. Sarter, Woods, & Billings (1997) indicate that pilots pointed out situations in which they became worried about their behavior due to cockpit automation, which affected their focus and diverted their attention from other tasks on hand.

Numerous studies have suggested ideas to overcome the challenges with cockpit automation. Sumwalt (2003) proposes designing precise procedures for pilots to actively monitor automated cockpit systems, and Casner & Schooler (2014) propose developing automated systems that can "check-in" pilots by challenging them with tasks that can bring the pilots back in the loop. A follow up study by Canser (2006) shows that even routine talk among pilots about their position and heading was enough to counteract the "out-of-the-loop" effects caused by using advanced cockpit automation systems. One thing missing in the studies is the integration of augmented cognition systems with the automation systems in aircraft cockpits. In our study, we test the efficacy of such systems.

2 Literature Review

2.1 Aviation Accidents Analysis

We collected data on aviation accidents from databases maintained by the National Transportation Safety Board (NTSB), the Aviation Safety Network (ASN), and PlaneCrashInfo.com to identify common pilot errors that led to aviation accidents.

2.1.1 NTSB Aviation Accident Reports

The NTSB's aviation accident database (National Transportation Safety Board, 2014) contains information on civil aviation accidents and selected incidents in the United States, its territories and possessions, and international waters dating to 1962. As of June 2014, the database included more than 72,000 accident and incident reports. The NTSB determines the probable causes of each accident and issues safety recommendations aimed at preventing similar accidents.

The database is organized by event (i.e., an accident or incident) and includes tables, one of which contains a narrative field that identifies the probable cause of each accident or incident and presents a many-to-one relationship with other tables. Using IBM's Many Eyes visualization technology word tree (IBM Co., 2014), we analyzed the probable causes as identified in the narrative fields.

A word tree is a visual search tool for unstructured text, such as a book, article, or speech (IBM Co., 2014). It allows the user to choose a word or phrase and retrieves all the occurrences of the word or phrase, along with the phrase that follows it. Context is arranged in a branching format to reveal recurrent themes and phrases.

Figure 1 shows a word tree created from the narratives table of the NTSB's database for the period January 2000 to June 2014 by using the search term "pilot's". Font size represents how often the word or phrase is used. Here, the word "pilot's" occurs frequently, accompanied by phrase "failure", which also occurs frequently (International Business Machines Corporation, 2014). For instance, "failure" follows "pilot's" many times, as do "inadequate" and "improper."

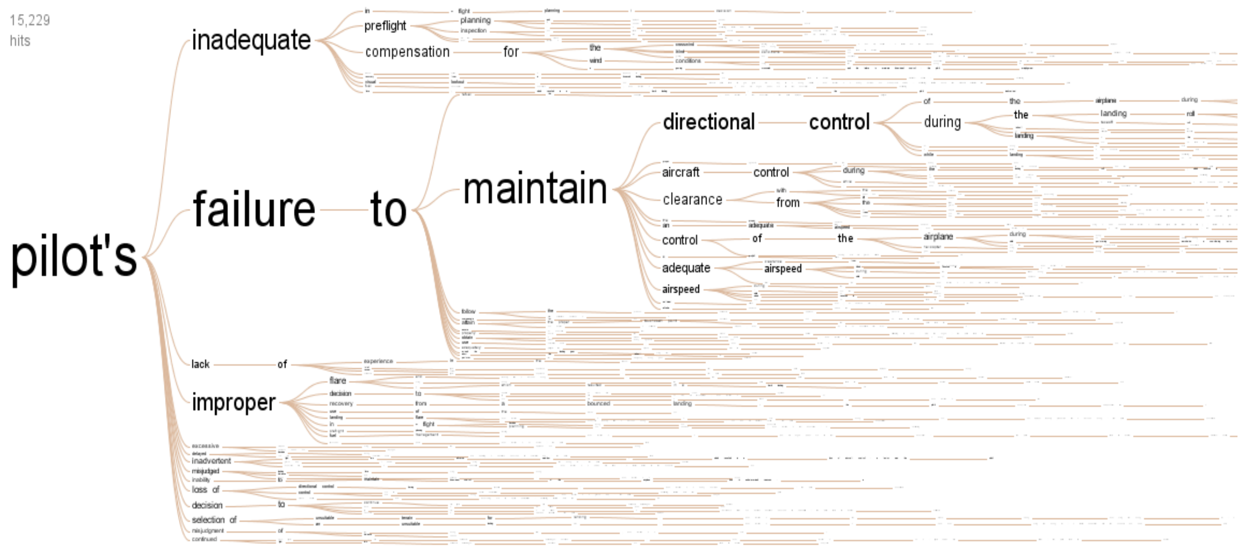


Figure 1. IBM Word Tree

Going a step further, a fishbone diagram in Figure 2 shows the main causes of aviation accidents. Red indicates the types of errors by pilots that caused the majority of aviation accidents. As Figure 2 shows, some of the main pilot errors are misjudgments, delayed decisions, failure to follow the procedures, failure to maintain aircraft control, and failure to maintain proper airspeed.

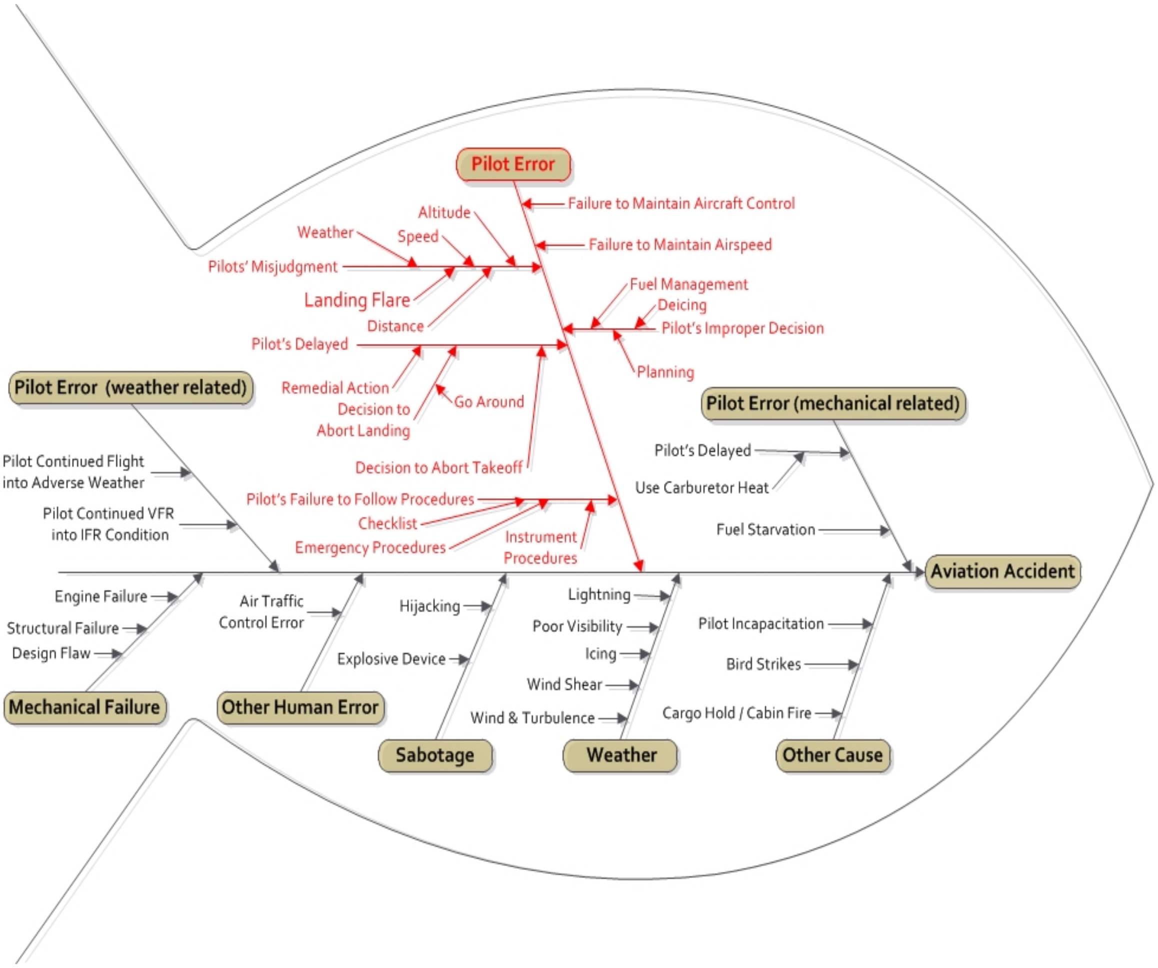


Figure 2. Fishbone Diagram Shows Causes of Aviation Accident from January 2000 to June 2014

2.1.2 Aviation Safety Network (ASN) Reports

The ASN Safety Database (Aviation Safety Network, 2015), which is updated every week, contains information on more than 15,800 commercial, military transport, and private aircraft safety occurrences since 1921. For the purposes of this study, we considered accidents involving aircraft capable of carrying at least 12 passengers for the period from January 2000 to June 2014.

Figure 3 presents the number of hull-loss accidents and fatalities per year for each flight phase for commercial, corporate, and military transport aircraft.

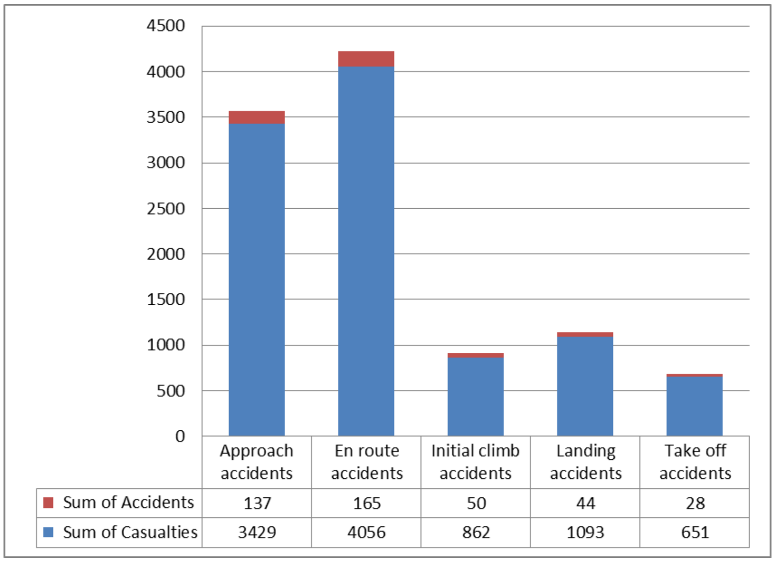


Figure 3. Aviation Accidents by Flight Phases

2.1.3 PlaneCrashInfo.com Reports

This database includes all civil and commercial aircraft accidents of scheduled and nonscheduled passenger airliners worldwide that resulted in a fatality (including all U.S. Part 121 and Part 135 fatal accidents) (Plane Crash Info Database, 2014). Figure 4 includes data from 1950 to June 2014 for 1,085 fatal accidents worldwide involving commercial aircraft for which a specific cause is known. It does not include aircraft with 18 or fewer people aboard, military aircraft, private aircraft, or helicopters (Plane Crash Info Database, 2014).

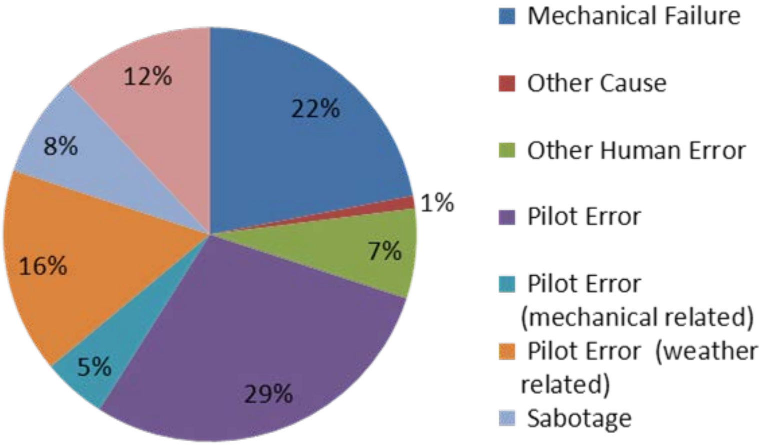


Figure 4. Causes of Fatal Accidents

2.2 Current research in Aviation Safety and Augmented Cognition Systems

Several U.S. Government agencies, such as the Department of Defense and the National Aeronautics and Space Administration (NASA), have used augmented cognition (AugCog) applications in flight contexts to enhance pilot perception through synthetic vision technology (Prinzel et al., 2014) and increased situation awareness (Foyle, Andre, & Hooey, 2005). NASA has also investigated AugCog's ability to reduce workload and manage data overload. Interest is growing in the private sector as well. Systems architecture and follow-on techniques that detect and analyze a subject's workload have been used in commercial notification and communication systems.

Improvements in human cognition are particularly valuable when human mistakes can cause serious accidents, as with aircraft pilots. For instance, pilot errors may be linked to the pilot's inappropriate allocation of attention resources. Research on attention allocation has shown that, when a human operator is faced with several decisions that require similar processing resources, there are typically tradeoffs in making these decisions (Adams, 2005).

Advancements in information technology have led to the development of complex systems that have highly interrelated components. Although this advancement has significantly increased efficiency and resulted in the development and operation of enhanced systems, it has also meant greater work overload and posed the danger of system-induced catastrophes. Perrow (1984) argues that highly coupled complex systems with highly interdependent components are inherently unstable and disposed to massive failure. This potential instability has made human factors-based evaluation even more important than previously.

To avoid common human errors, today's aviation training covers many of the lessons learned from human factors research on aviation accidents. For example, threat and error management (TEM) is emphasized. TEM recognizes that, even when flights are planned and operated by trained pilots in collaboration with dispatchers, mechanics, flight attendants, and others, human beings still make mistakes, especially when the environment presents challenges. TEM trains pilots to recognize errors as quickly as possible and manage or mitigate their negative impact (Federal Aviation Administration, 2012).

2.3 The Cognitive Cockpit

In the late 1990s, the British Ministry of Defense group QinetiQ created the cognitive cockpit, or "CogPit" (Adams, 2005). CogPit is a test bed for researching and documenting automated decision support and AugCog systems in single-seat aircraft. QinetiQ's vision is to create and implement a "trustworthy automation" that can be sensitive to context (Adams, 2005). Pilot data and aircraft sensors are used to create a series of tasks that can either be automatically executed or directed to the pilot through display messages. The current CogPit simulator includes software that analyzes the pilot's workload through such measures as electroencephalography (EEG) and control inputs (Adams, 2005; Foyle et al., 2005; Prinzel et al., 2014). In the planning process, the pilot chooses from six automation levels, ranging from fully manual to fully automatic. Risk mitigation includes master-arm switch automation, defensive-aids-suite activation, and targeting-pod execution (Adams, 2005).

QinetiQ tested the CogPit system using six pilots in six multisegment air-to-ground missions. As cognitive loads increased, automation levels increased. Results suggest that cognitive augmentation improves survivability (Adams, 2005). However, additional trials are needed to assess the efficacy of cognitive augmentation.

The US Naval Air Systems Command (NAVAIR) human-systems integration lab partnered with BMH Associates, Inc. (now Alion Science and Technology) to conduct similar research and has now tested eight pilots during a simulated close-air-support mission (Adams, 2005). Pilots were connected to electroencephalography (EEG), electrocardiogram (EKG), and electrooculography (EOG) sensors and simulated a 10-minute flight over a target area with the mission to identify and destroy up to four enemy tanks while avoiding surface-to-air missiles (Adams, 2005). Pilot-approved mitigations for the mission included automated chaff release and slewing to the target. Afterward, each pilot flew four similar missions without decision support and four with decision support using randomly deployed mitigations. The study's goal was to demonstrate at least a 50 percent improvement in targeting and 50 percent decrease in friendly fire compared to baseline data (Adams, 2005). As of this writing, final results have not been released, but preliminary results show a 200 percent increase in targeting and no incidents of friendly fire (Adams, 2005).

The Defense Advanced Research Projects Agency (DARPA) also has used augmented cognition to develop innovative technologies that will transform human-machine interaction by making information systems sensitive to the capabilities and limitations of the human component of the system. By measuring individual human capabilities while being sensitive to human limitations, the DARPA study demonstrated that an augmented cognition system can improve overall system performance by an order of magnitude (St. John, Kobus, Morrison, & Schmorrow, 2004). Many advances in the field of cognitive science and understanding of human decision making have recently been made (St. John et al., 2004). Advancements in sensor technologies for measuring brain activity and various facets of cognition have facilitated how information is presented to the human operators of complex systems. Despite all the progress with sensor technologies, uncertainty remains about the accuracy of the information collected by cognitive sensors and their interconnectivity and practicality.

2.4 Common Areas in Current ACS Research

In general, AugCog uses methods and designs that combine computation and knowledge about human limitations to address biases and shortfalls in human cognition. It does this by continuously assessing the user's context (e.g., in the case of a pilot, attention, workload, and stress) and learning to recognize the trends, patterns, and situations relevant to the user's context and goals. An AugCog system must include at least four components:

1. Sensors for determining the user state
2. An inference engine or classifier to evaluate incoming sensor information
3. An adaptive user interface, and
4. An underlying computational system architecture to integrate these components (Schmorrow & Kruse, 2004).

An entirely functioning system would have several more components, but the four listed above are the most important for inclusion in an augmented cognition system. Separately, each of these components is straightforward. Much of the current augmented cognition research seeks to close the loop by incorporating these components and build computational systems that adapt to the user. Although researchers are using more complex sensors, the challenge with these systems is not the sensing component. Rather, it is precisely predicting and assessing information from the sensors—namely, identifying the user's state and choosing a suitable strategy to aid the user at that point.

For an ACS to work well, it should recognize at least one of these sensing shortfalls in real time and improve it in the course of a performance-improving alleviation strategy. These alleviation strategies are presented to the user in the course of the adaptive interface and may involve modality switching (between visual and auditory), intelligent interruption, task negotiation and scheduling, and assisted context retrieval via bookmarking (Schmorrow & Kruse, 2004). When a user condition is properly sensed, a suitable strategy is chosen to ease the shortfall, the interface is modified to perform the strategy, and the resulting sensory information confirms that the function has worked. Only then has a system closed the loop and effectively augmented the user's cognition.

Despite all the advances in technology, many constraints remain: equipment efficiency, cost, size, power consumption, and pilot comfort, among others.

3 Proposed Augmented Cognition System

As technology advances in avionics, automation, and computing processes, cockpit systems become increasingly complex. To overcome the limitations described above, we integrated an ACS into an aircraft's flight management system (FMS), which Figure 5 shows.

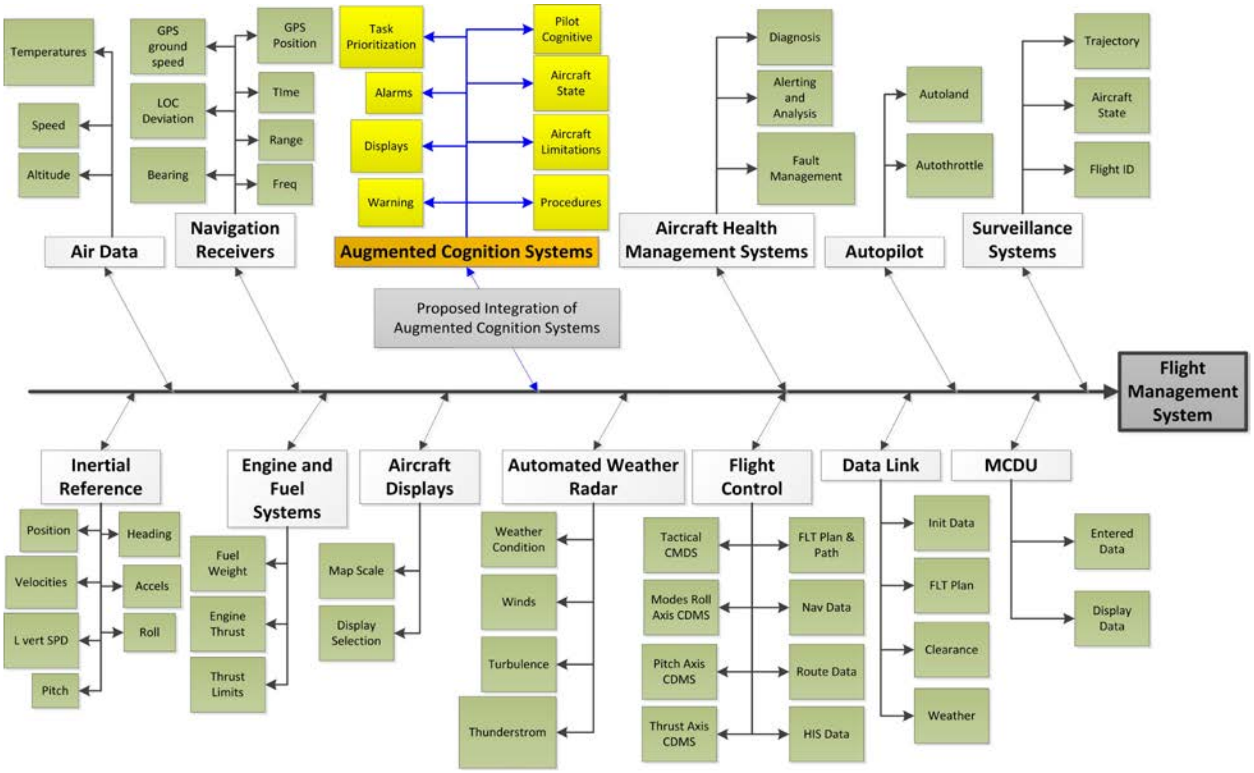


Figure 5. Integration of Augmented Cognition into a Flight Management System

The integration of an ACS in the FMS will allow the ACS to access data collected from multiple systems (e.g., GPS, VOR, weather radar, autopilot, aircraft health management systems, flight controls, etc.). The ACS can cross-reference this data with data collected from other instruments and with the data saved in the flight management database (aircraft limitations, performance, procedures, flight plan, etc.). All such data are major elements in augmented cognition's decision making and risk-assessment tools.

This process allows the ACS to precisely assess the aircraft's state at each segment of the flight. By using the ACS's decision making and risk-assessment algorithm, the ACS prioritizes pilot tasks and provides instruction via voice and display. Pilot and aircraft performance are measured against a set of standard procedures and limitations (as specified by the FAA, airline, and aircraft manufacturer) as a nominal base. Throughout the flight, from takeoff to landing, the ACS uses GPS, VOR, radar, and other navigational guidance to collect additional information, and, by employing the decision making and risk-assessment algorithm, locate the aircraft's position. The ACS system cross-checks this with the flight plan, then assesses the state of the aircraft and current segment of the flight (a basic GPS function). Using the cross-referencing processes with information from other instruments—airspeed, ground speed, true speed, altitude, weather conditions, wind, air pressure, thrust, aircraft health, ILS, and so on—and the flight plan, the ACS identifies the next segment in the flight plan. Based on feedback from the decision making and risk-assessment algorithm, the system can prioritize procedures and pilot tasks before entering the new flight segment. Relevant procedures, such as those required for landing, and limitations, such as altitude and airspeed, are then communicated to the flight crew by display and voice. The aircraft can be controlled either manually or by autopilot.

The ACS also checks aircraft and pilot performance against the set of procedures and limitations. It notifies the pilot of any system failure, emergency, or deviation from the aircraft's limitations and procedures by issuing an alarm and warnings by voice and display. For example, before entering the final approach for runway 19L at Dulles International Airport, the ACS uploads the approach plate for the selected runway from the database and briefs the pilot by voice and display. The system then provides instructions to assist the pilot in reconfiguring the aircraft for the approach segment of the flight by using the flight procedures designed by the manufacturer and airline. The ACS prioritizes these procedures and announces relevant limitations (e.g., maximum and minimum airspeed for entering the approach) well in advance of arrival at the entry point and triggers an alarm if the aircraft starts to diverge from the procedures. In other words, the ACS creates a virtual tunnel in the flight path and assists the pilot in staying in this and other limitations by increasing the pilot's situational awareness and attention allocation and reducing the pilot's workload through task prioritization. Due to space limitations for this paper, Figure 6 presents only a simplified ACS workflow for a flight's descent and approach segment.

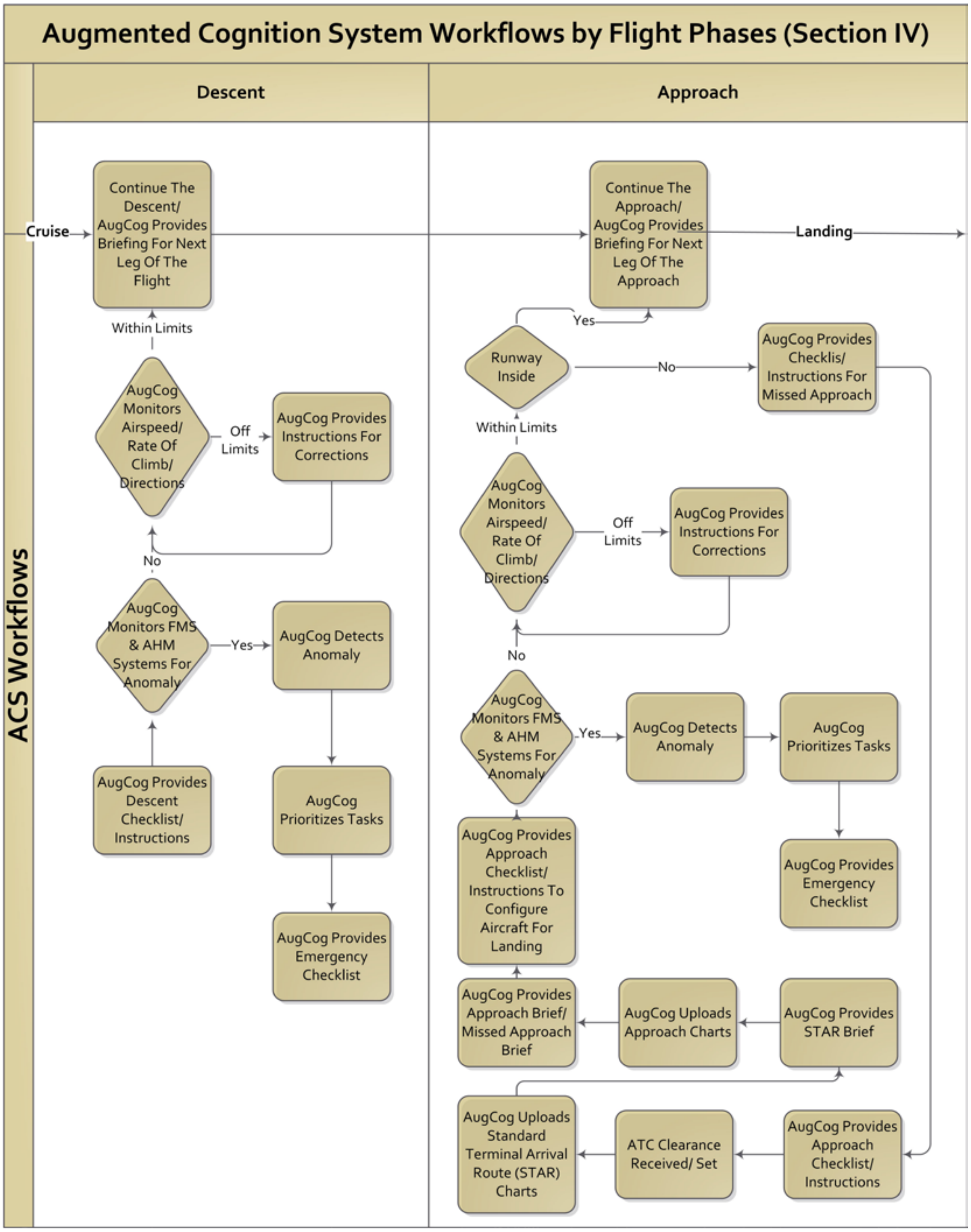


Figure 6. Simplified ACS Workflow

The pilot's workload and opportunities for errors increase significantly during the approach and landing segments of the flight. The pilot's workload also significantly increases under instrument flight rules (IFR), which govern a flight whenever flight by visual reference is not safe. Based on previous studies and data from FAA and NTSB accident reports (National Transportation Safety Board, 2014), flying under IFR conditions and during the last segment of the flight path (approach and landing) are the two conditions under which the pilot's workload increases the most. Because the opportunities for errors increase correspondingly, most aviation accidents are attributed to human errors under these conditions. The pilot's workload becomes saturated as the pilot scans flight-deck instruments, sets flight controls and automation for approach and landing, communicates with the control tower, and follows a plethora of other procedures. Therefore, chances for human errors increase as well. The proposed ACS assists the pilot by constantly assessing the performance of both the pilot and the aircraft and providing feedback via the closed-loop system. It prioritizes the pilot's tasks in a timely manner and not only issues alarms and early warnings, but also uses the decision making and risk-assessment algorithm to provide instructions for optimal corrective actions. This method increases the pilot's situational awareness and attention allocation by combining augmented cognition with automation systems while simultaneously using other avionic technology to manage and increase pilot performance and avoid human errors.

4 Problem Statement

Despite all the advancement in aviation technology and cockpit automation, aviation accidents still occur. As the earlier sections indicate, human factors are still the major cause of aviation accidents. Cockpit automation poses a risk of disengaging the pilot in the cockpit, introducing a great risk of increasing human errors in aviation. Therefore, this study proposes integrating ACS in aircraft FMS and tests its functionality and measures the pilot's performance improvements.

4.1 Theory and Hypothesis

Scientists have established systematic models of memory, thinking, and cognition. The most recognized model is the information processing model (IPM). This model has been framed around three key components: sensory memory, working memory, and long-term memory (Halpern, 2003).

Humans can process a limited amount of incoming information in sensory and working memory, while long-term memory is used for storing information and knowledge. In the sensory memory, sensory information will be processed for a very short time, usually about half a second to 3 seconds. The sensory information held in the sensory memory is very limited, usually about five to seven discrete elements such as alphabetic letters. Therefore, if a person sees 10 letters simultaneously for 1 second, the person will most likely remember only five to seven of those letters. The key function of sensory memory is to receive and sort incoming stimuli and process those stimuli that are most applicable at that time (Schraw & McCrudden, 2013).

Scientists have concluded that information processing in sensory memory typically happens too fast for people to consciously control what they attend to. In other words, attention allocation and sensory processing take place very quickly and may occur without conscious control.

There are two types of information that have higher chances of being processed in sensory memory: first, relevant information to the task at hand and, second, information that is familiar and subject to automatic processing. If relevant information is critical to a task, it may receive some degree of control or conscious processing. However, a limited amount of such information can be processed at any given time in sensory memory (Schraw & McCrudden, 2013).

There are two possible scenarios when stimuli enter sensory memory: they are either forwarded to working memory or removed from the memory. Working memory refers to a temporary multi-component memory in which meaning is assigned to it and it would be linked to other information pieces.

Automaticity is another important term in IPM. This term describes the ability to perform a task very fast due to repeated practice (Stanovich, 2003). Such activities typically need less cognitive resources. An example of such activities is monitoring cockpit instruments while the aircraft is flying on an auto-pilot mode. Another key term is selective processing, which describes focusing one's limited cognitive resources deliberately on the most relevant stimuli to the task at hand.

The theory underlying the ACS is to assist pilots with recognizing incoming stimuli in the sensory memory such that the ACS supplements the function of the sensory memory. In this process, the ACS works as an external sensory memory that receives and sorts incoming stimuli and processes those stimuli that are most applicable to the present time. The ACS provides instructions related to relevant information to the task at hand and familiar information that is subject to selective and automatic processing. These instructions will be forwarded to the working memory and, because they are subject to automaticity in processing, such activities typically need less cognitive resources, consequently assisting pilots in terms of task allocation, attentional resources, situational awareness, and workload management.

Hence, integrating augmented cognition with automation systems in the aircraft cockpit reduces human/pilot errors in aviation. Therefore, this study tests the following hypothesis:

Hypothesis: Integrating augmented cognition with automation systems in the aircraft cockpit will decrease human/pilot errors in aviation.

5 Experiment and Simulations

We used a within-subjects experimental design to assess the efficacy of the proposed ACS. All subjects carried out an aviation task (to be described later) twice, once without ACS and once with ACS. They first carried out the task without ACS, then with ACS, and we compared the results across both conditions. To minimize learning effects, we designed the air traffic control clearances slightly differently and incorporated a time gap between both flights.

Eighty-seven accidents involving scheduled Code of Federal Regulations (CFR) Part 135 commuter and on-demand flights in the US for which the probable cause is known were reported in the NTSB database from January 2000 to December 2013 (National Transportation Safety Board, 2014). Also reported were 613 nonscheduled Part 135 accidents in the US for the same period for which the probable cause is known.

Based on the information extracted from probable causes of these accidents, we can divide them into 10 categories for which the pilot (i.e., human factor) was the primary cause of the accident:

1. Pilot's disorientation
2. Weather affecting pilot's decisions and performance
3. Pilot's failure to follow procedures
4. Pilot's failure to maintain adequate airspeed
5. Pilot's failure to extend the landing gear
6. Pilot's failure to maintain appropriate rate of descent
7. Pilot's failure to maintain appropriate direction
8. Pilot's failure to maintain adequate distance/altitude from terrain
9. Pilot's failure to maintain appropriate fuel management, and
10. Pilot's failure to maintain a stabilized approach with adequate vertical and lateral tracks.

To test and validate the proposed aircraft ACS, we designed a flight scenario using FAA practical test standards and used a flight simulator to introduce examples of the above accident-causing factors during a simulated flight. Unpredicted errors by test pilots were identified and measured throughout the scenario, and overall pilot performance and flight precision were measured to assess flight improvement.

5.1 Simulated Flight Scenario

A flight from Baltimore Washington International Airport (BWI) to Dulles International Airport (IAD) was simulated under IFR conditions. The same scenario, which included a number of out-of-sequence events, was repeated twice with each test pilot. The first flight was conducted using standard airplane flight instruments—specifically, the Garmin G1000 Integrated Flight Management System. The second flight was conducted using the Garmin G1000 integrated with the proposed ACS. In-flight emergency scenarios were not described beforehand to test pilots. The test pilots were briefed on weather conditions, flight plan, and all other standard procedures for aircraft.

Simulated weather conditions at BWI consisted of humidity 46 percent, wind speed 15 miles per hour from 230 degrees, barometer 30.40 inches (1029.4 mb), dewpoint at 34 degrees Fahrenheit (1°C), visibility at 7 miles, scattered clouds at 3500 feet Altitude above Ground Level (AGL), and winds aloft at 3000 feet from 280 degrees at 28 knots, 6000 feet from 290 degrees at 35 knots, 9000 feet from 290 degrees at 37 knots, and 12000 feet from 290 degrees at 41 knots.

Simulated weather conditions at IAD consisted of humidity 41 percent, wind speed 18 mph at 210 degrees, barometer 30.40 inches (1029.4 mb), dewpoint at 38 Fahrenheit (4°C), visibility at 5 miles, scattered clouds 2500 feet AGL, and winds aloft at 3000 feet from 230 degrees at 25 knots, 6000 feet from 240 degrees at 31 knots, 9000 feet from 240 degrees at 35 knots, and 12000 feet from 240 degrees at 37 knots.

During the flight, test pilots were required to communicate with air traffic controllers, navigate, and control the flight safely to the destination. After departing BWI, a crosswind of 35 kn to 45 kn was introduced with icing conditions at 4000 feet and above. As stated earlier, all flights were under IFR conditions. As the pilot climbed to 4000 feet, the simulator introduced a pitot/static system failure due to icing, which affects the airspeed indicator and the altimeter indicator. As a result of the low speed, the stall-warning system was activated. The pilot's performance and response to the failures and warning were measured under both scenarios, and the precision of the flight was measured by the flight simulator.

Throughout the flight the simulator measured airspeed, true airspeed, vertical speed (rate of climb/descent), horizontal position, and overall flight precision. Later in the flight, turbulence was introduced to increase the pilot's workload. The pilot was cleared to land at IAD using the standard GPS approach, at which time the low-fuel warning came on. As the pilot entered the approach and landing segment of the flight, the accuracy of the procedures and flight path were monitored.

In the second scenario, after activating the flight plan, the ACS performed the following functions to assist the pilot:

1. Prioritized the pilot's tasks
2. Provided instructions and procedures prior to each active task
3. Provided warnings, alarms, and corrective actions in case of any nonconformity with airplane limitations or navigation or deviation from the flight plan, and
4. Monitored the flight and provided feedback to the pilot.

5.2 Study Sample

The study sample included 15 commercial (CML) and flight instructor (CFI, CFII, MEI, CFIG, and ATP) certificate holders with instrument ratings and high performance ratings. The minimum flight time requirement for this study was 500 hours (qualification requirement for regional airlines).

5.3 FAA Practical Test Standard Concept

Title 14 Part 61 of the CFR specifies the knowledge and skills an applicant must demonstrate to qualify for an instrument rating. The CFR permits the FAA to publish practical test standards (PTS) that cover the areas of operation and specific tasks in which pilot competency must be demonstrated (Federal Aviation Administration, 2012). Adherence to the provisions of the regulations and PTS is mandatory for evaluating instrument-rating applicants.

To evaluate the effectiveness of the proposed augmented cognition system, we used FAA PTS standards to measure the precision of flight maneuvers.

5.4 Use of the Practical Test Standards

The flight scenario included all the areas of operation and tasks required by the FAA for the airplane commercial instrument rating and allowed for evaluation of as many required areas of operation and tasks as possible without disruption. During the mission, the study interjected problems and emergencies that the test pilot was required to manage so that most of the areas of operation and tasks could be accomplished during the mission. It also afforded the flexibility to change the scenario to accommodate unexpected situations as they arose.

6 Validation and Data Analysis

The study collected four types of data: (A) pilot demographics and qualifications, (B) survey responses, (C) flight precision with no augmentation, and (D) flight precision with augmentation.

We used a paired t-test to compare two population means where we had two samples in which observations in simulation without ACS can be paired with observations in the simulation with ACS to find out if the integration of the ACS lead to improvements in the pilot's use of the checklist, situational awareness, and flight precision. We used the results from this paired t-test to draw conclusions about the impact of this ACS module in general. Therefore, to analyze the main hypothesis, "Integrating augmented cognition with automation systems in the aircraft cockpit will decrease human/pilot errors in aviation", we divided the main hypothesis into four sub-hypotheses:

H1: Integrating augmented cognition with automation systems in the aircraft cockpit will decrease pilots' errors in airspeed controls.

H2: Integrating augmented cognition with automation systems in the aircraft cockpit will decrease pilots' errors in heading/directional controls.

H3: Integrating augmented cognition with automation systems in the aircraft cockpit will decrease pilots' errors in altitude controls.

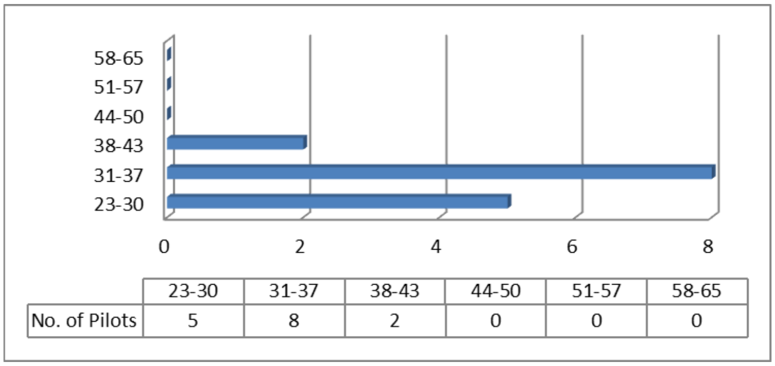
H4: Integrating augmented cognition with automation systems in the aircraft cockpit will decrease pilots' errors in course/radial/bearing controls.

Let X = observations without ACS, Y = observation with ACS. To test the hypothesis this study used the following procedure:

1. Calculate the difference $(d_i = y_i - x_i)$ between the two observations on each pair.
2. Calculate the mean difference, $\overline{d}$.
3. Calculate the standard deviation of the differences, S_d , and use this to calculate the standard error of the mean difference, $\mathrm{SE}(\overline{d}) = \frac{S_d}{\sqrt{n}}$., when n = number of observations.
4. Calculate the t-statistic, which is given by$T = \frac{\overline{d}}{SE\ (d)}$. Under the hypothesis, this statistic follows a t-distribution with n − 1 degrees of freedom.
5. Use tables of the t-distribution to compare the value for T to the t_{n-1} distribution. This presents the p-value for the paired t-test.

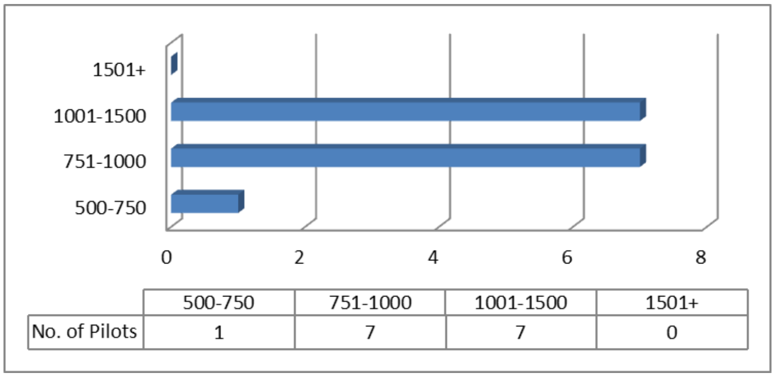
6.1 Pilot Demographics

We extracted the following data from test pilots' records: sex, age, hours of flight time, pilot certifications, and number of flights in the last 90 days. All of them were male. Figure 7 shows the distribution of test pilot ages. Figure 8 shows their hours of flight time. Figure 9 shows the pilot certifications, and Figure 10 presents the number of flights they had piloted in the last 90 days.



	23-30	31-37	38-43	44-50	51-57	58-65
No. of Pilots	5	8	2	0	0	0

Figure 7. Pilot's Age



	500-750	751-1000	1001-1500	1501+
No. of Pilots	1	7	7	0

Figure 8. Total Pilot in Command (PIC) Hours

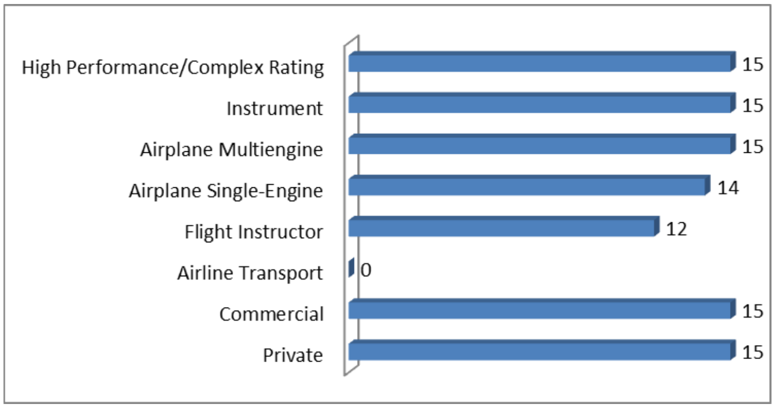
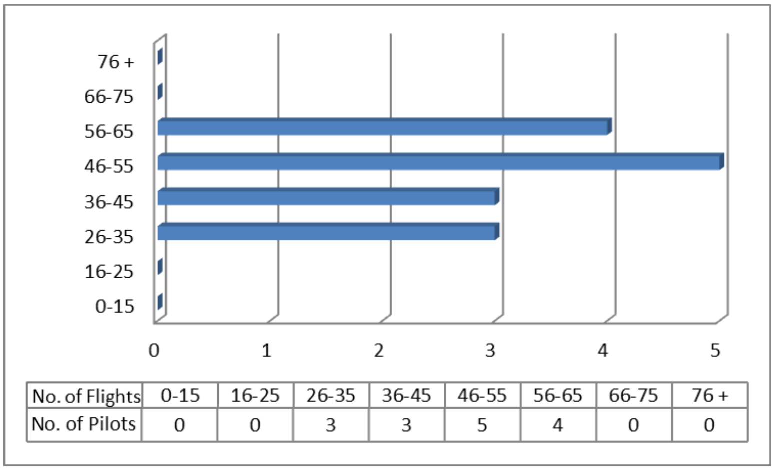


Figure 9. Pilot Certifications



No. of Flights	0-15	16-25	26-35	36-45	46-55	56-65	66-75	76 +
No. of Pilots	0	0	3	3	5	4	0	0

Figure 10. Number of Flights in Last 90 Days

6.2 Survey Responses

As Figure 11 shows, in response to the question “Overall, how would you rate your level of intellectual challenge with this augmented cognition system?”, the majority of test pilots indicated that they were not intellectually challenged by the augmented cognition system.

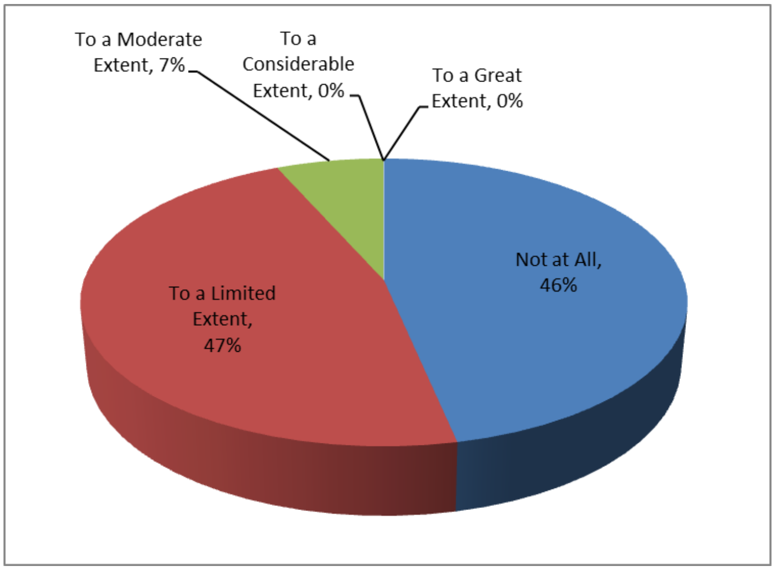


Figure 11. Level of Intellectual Challenge

As Figure 12 shows, in response to the question “Did the use of augmented cognition system in the second flight increase your situational awareness?”, the overwhelming majority of pilots (87 percent) indicated that the ACS in the second flight increased their situational awareness to a great extent. The rest of the pilots (13%) indicated that the ACS increased their situational awareness to a considerable extent.

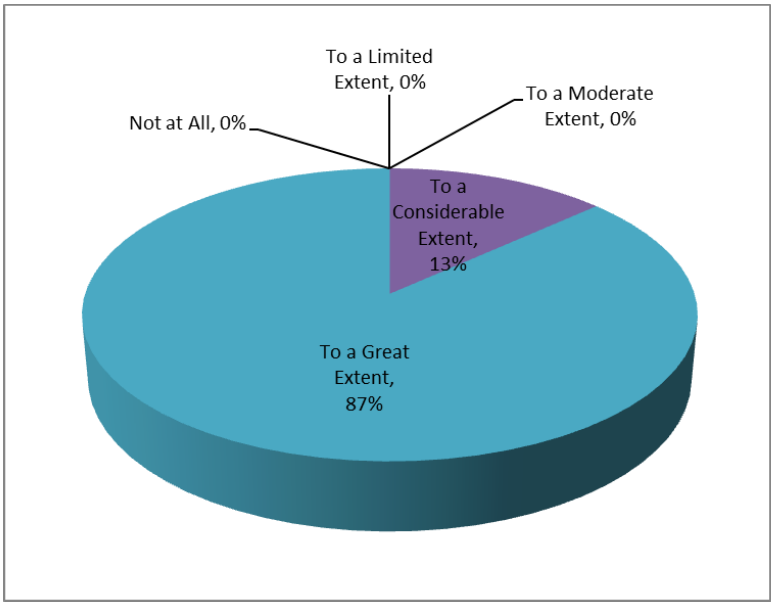


Figure 12. Situational Awareness

As Figure 13 shows, in response to the question “Was the augmented cognition system’s instructions organized in a manner that helped to reduce your workload in the cockpit?”, 46 percent of test pilots indicated that the ACS instructions were organized in a manner that reduced their workload to a great extent, followed by 46 percent to a considerable extent, and 8 percent to a moderate extent.

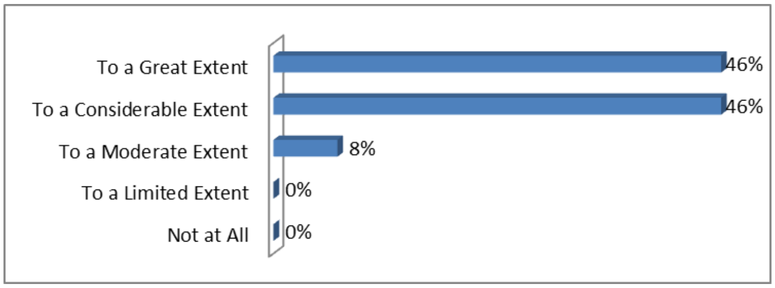


Figure 13. Flight Workload

As Figure 14 shows, 40 percent of pilots indicated that the ACS instructions were organized in a manner that helped to prioritize their tasks in the cockpit to a great extent, followed by 53 percent to a considerable extent, and 7 percent to a limited extent.

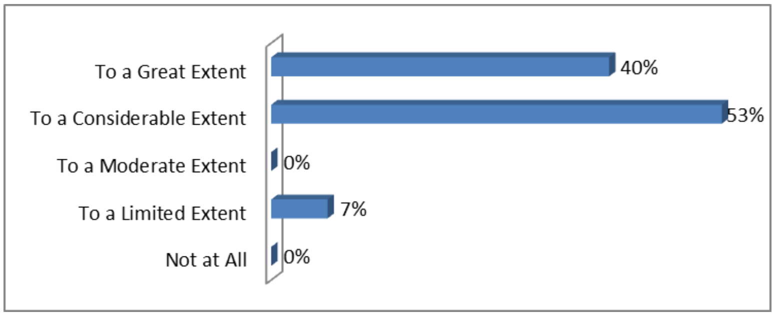


Figure 14. Work Prioritization

As Figure 15 shows, regarding cockpit checklist and flight procedures, 87 percent of the pilots responded that the ACS instructions were organized in a manner that helped them to use cockpit checklists and follow flight procedures to a great extent and 13 percent to a considerable extent.

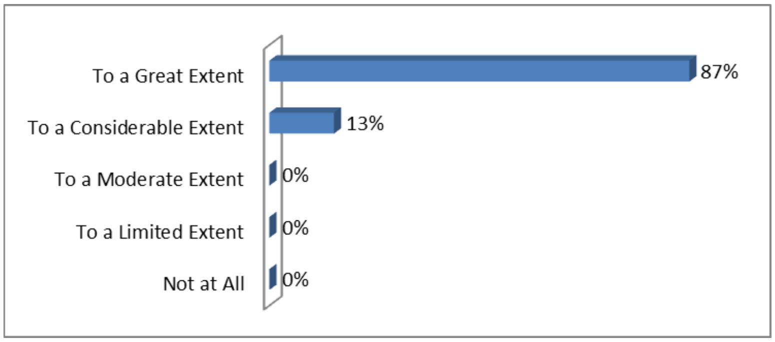


Figure 15. Use of Flight Checklist & Procedures

All of the pilots were strongly in favor of integrating the proposed ACS into cockpits. As previously shown, they reported that the proposed ACS had significantly increased their situational awareness and helped them to fully comply with cockpit checklists and procedures. As Figure 16 shows, all of them recommended integrating the ACS in future cockpit design to a great extent.

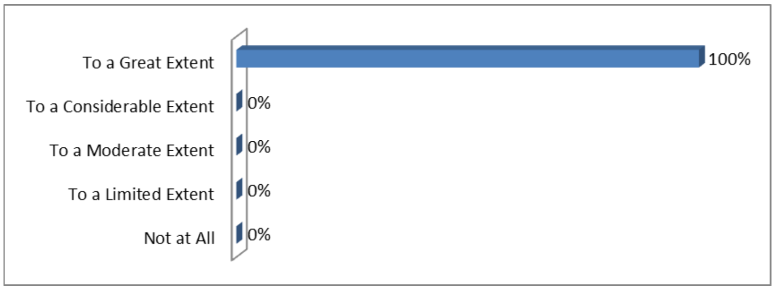
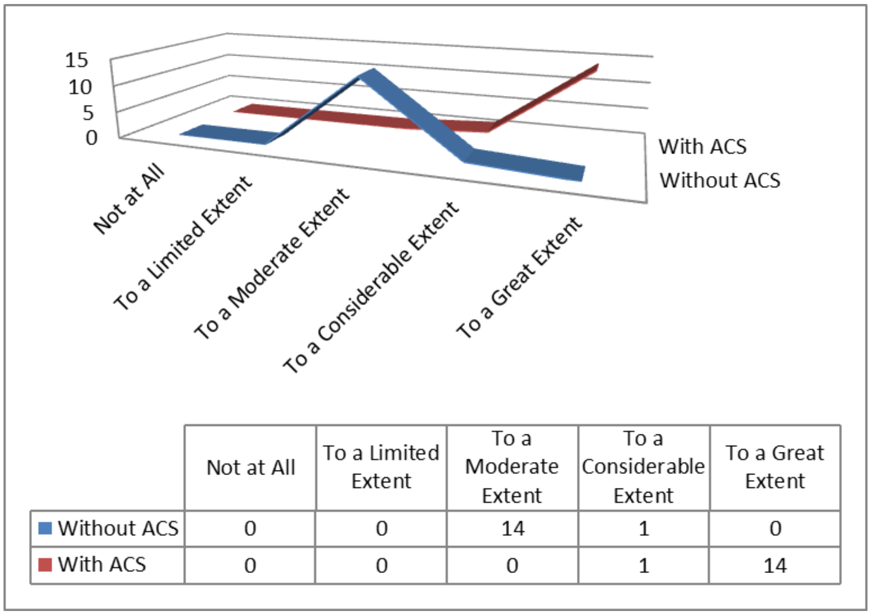


Figure 16. Integration of ACS in Future Cockpit Design

6.3 Flight Precision with and without Augmentation

We collected data on flight precision from the simulator, which measured use of cockpit checklists, adherence to procedures, and flight precision. In the first flight, the simulation used standard instruments with no ACS, and, in the second flight, the ACS was added to the standard instruments. Flights were divided into four segments: departure, en-route, approach, and arrival. Flight precision during each segment was measured in accordance with Title 14 of the CFR, Part 61, along four axes: (1) altitude, (2) course, (3) radial/bearing, and heading, and (4) airspeed.

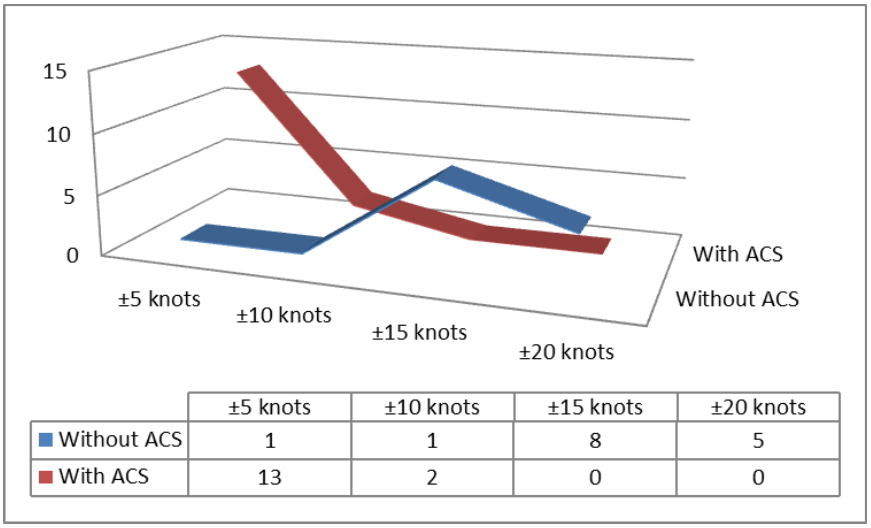
In the first simulation (without ACS), 92 percent of the pilots used cockpit checklists and adhered to procedures to only a moderate extent, and 8 percent to a considerable extent. In the second simulated flight (with ACS), 92 percent used cockpit checklists and adhered to procedures to a great extent and 8 percent to a considerable extent—a significant improvement (see Figure 17).



	Not at All	To a Limited Extent	To a Moderate Extent	To a Considerable Extent	To a Great Extent
🟦 Without ACS	0	0	14	1	0
🟥 With ACS	0	0	0	1	14

Figure 17. Use of Cockpit Checklists

In the first simulated flight (without ACS), flight-precision measurements showed that pilots complied with procedures and clearances in the standard tolerances as follows: 53 percent maintained the applicable airspeed within ± 15 knots, 33 percent within ± 20 knots, 7 percent within ± 10 knots, and 7 percent within ± 5 knots. In the second simulated flight (with ACS), 87 percent maintained the applicable airspeed within ± 5 knots, and 13 percent within ± 10 knots (see Figure 18). This is also a considerable improvement.



	±5 knots	±10 knots	±15 knots	±20 knots
🟦 Without ACS	1	1	8	5
🟥 With ACS	13	2	0	0

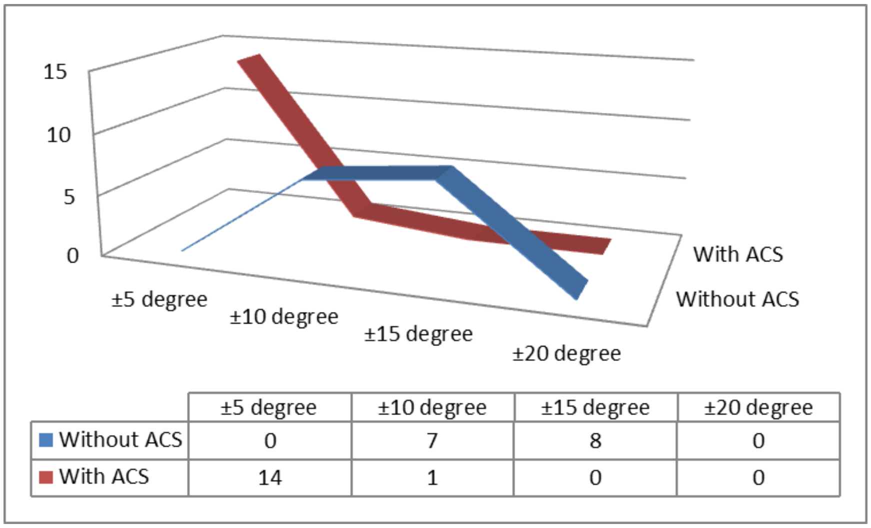
Figure 18. Airspeed

As Table 1 shows, the calculated mean for airspeed error from the designated airspeed observed from the simulator with ACS has dropped to 6.08 knots from 16.25 knots, which is the average mean of airspeed error without the ACS. This indicates a 2.67 times improvement, which is supported by a large t-value of 21.41. Hence, the first sub-hypothesis (H1) was supported ($p<0.01$), suggesting that integrating augmented cognition with automation systems in the aircraft cockpit decreases pilot errors in airspeed controls.

Table 1. Airspeed Error t-Test: Paired Two Sample for Means

	Without ACS	With ACS
Mean error	16.25	6.08
Variance	10.70	4.31
Observations	60.00	60.00
Pearson correlation	0.11	
Hypothesized mean difference	0.00	
df	59.00	
t stat	21.41	
P(T<=t) one-tail	0.00	
t critical one-tail	1.67	

During the first simulated flight (without ACS), 53 percent of pilots maintained the applicable headings within ± 15 degrees and 47 percent within ± 10 degrees. In contrast, 93 percent maintained the applicable headings within ± 5 degrees during the second flight (with ACS), and only 7 percent within ± 10 degrees (see Figure 19).



	±5 degree	±10 degree	±15 degree	±20 degree
🟦 Without ACS	0	7	8	0
🟥 With ACS	14	1	0	0

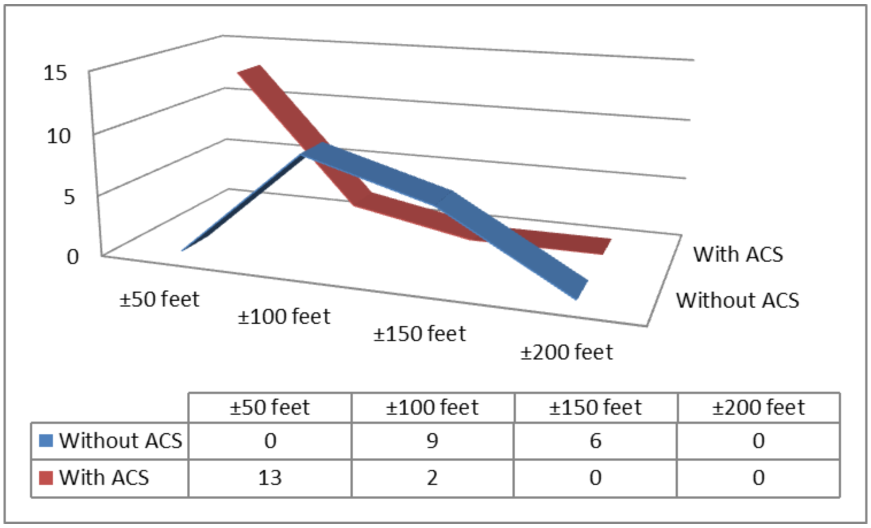
Figure 19. Headings

Table 2 shows that the calculated average mean of the heading error from assigned heading collected by simulator with ACS dropped to 5.75 degrees from 13.75 degrees, which is the average mean of heading error without the ACS. This indicates a 2.39 times improvement, which is supported by a large t-value of 23.51. Hence, the second sub-hypothesis (H2) was supported (p<0.01), suggesting that integrating augmented cognition with automation systems in the aircraft cockpit decreases pilot errors in heading/directional controls.

Table 2. Heading Error t-Test: Paired Two Sample for Means

	Without ACS	**With ACS**
Mean error	13.75	5.75
Variance	7.31	3.24
Observations	60.00	60.00
Pearson correlation	0.37	
Hypothesized mean difference	0.00	
Df	59.00	
t stat	23.51	
P(T<=t) one-tail	0.00	
t critical one-tail	1.67	

Sixty percent of the test pilots maintained the applicable altitude within ± 100 feet and 40 percent within ± 150 feet in the first flight (without ACS). In the second flight (with ACS), 87 percent maintained the applicable altitude within ± 50 feet and 13 percent within ± 100 feet (see Figure 20).



	±50 feet	±100 feet	±150 feet	±200 feet
🟦 Without ACS	0	9	6	0
🟥 With ACS	13	2	0	0

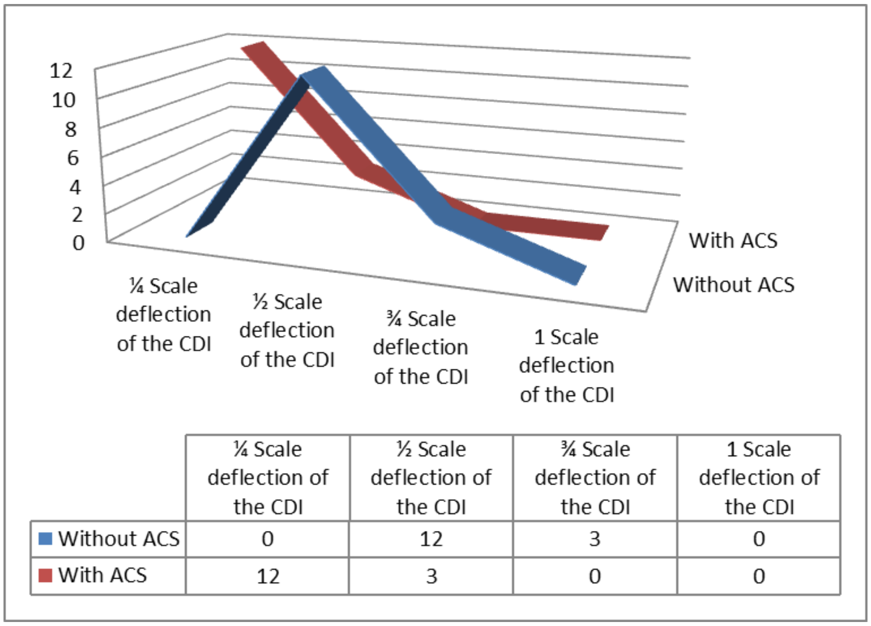
Figure 20. Altitude

Table 3 shows that the calculated average mean of the altitude error from the designated altitude collected by simulator with ACS has dropped to 58.33 feet from 137.50 feet, which is the average mean of altitude error without the ACS. This indicates a 2.35 times improvement, which is supported by a large t-value of 16.5. Hence, the third sub-hypothesis (H3) was supported ($p<0.01$), suggesting that integrating augmented cognition with automation systems in the aircraft cockpit decreases pilot errors in altitude controls.

Table 3. Altitude Error t-Test: Paired Two Sample for Means

	Without ACS	**With ACS**
Mean error	137.50	58.33
Variance	1239.41	353.11
Observations	60.00	60.00
Pearson correlation	0.16	
Hypothesized mean difference	0.00	
Df	59.00	
t stat	16.50	
P(T<=t) one-tail	0.00	
t critical one-tail	1.67	

In the first simulated flight, with no ACS, 80 percent of test pilots maintained the applicable course/radial/bearing within ± ½ scale deflection of the CDI, and 20 percent within ¾ scale deflection of the CDI. After integration of ACS in the second flight, 80 percent maintained the applicable course/radial/bearing within ± ¼ scale deflection of the CDI, and 20 percent within ½ scale deflection of the CDI—a 100 percent improvement (see Figure 21).



	¼ Scale deflection of the CDI	½ Scale deflection of the CDI	¾ Scale deflection of the CDI	1 Scale deflection of the CDI
🟦 Without ACS	0	12	3	0
🟥 With ACS	12	3	0	0

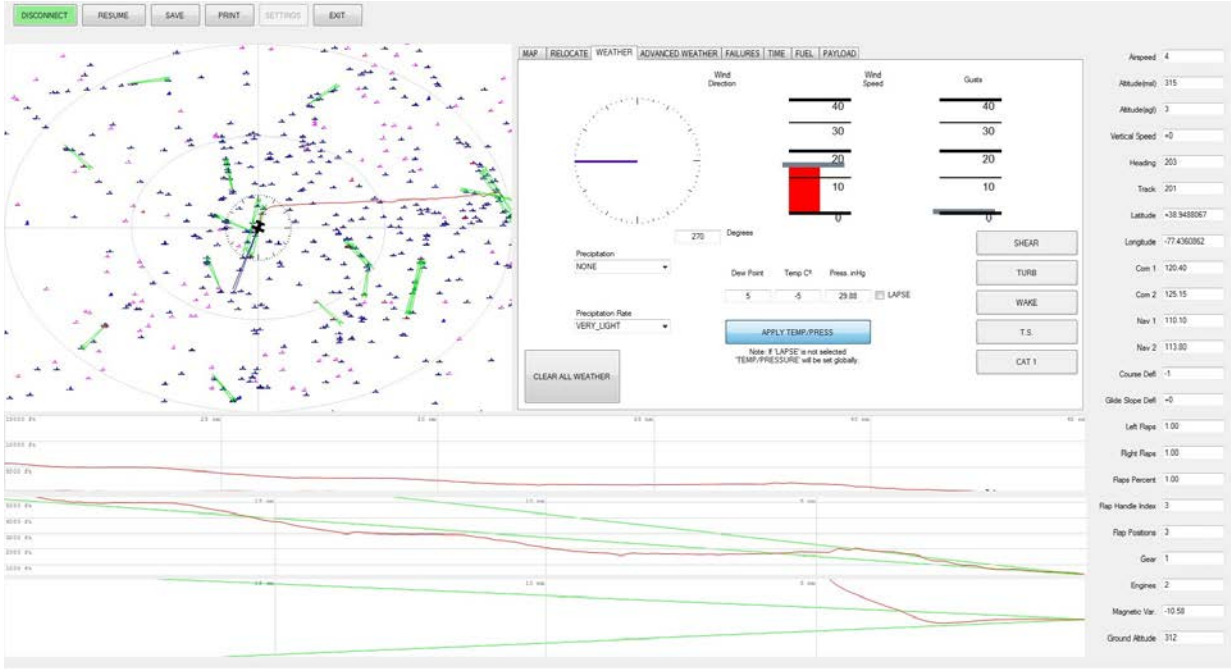
Figure 21. Course, Radial, or Bearing

As Table 4 shows, the calculated average mean of the course/radial/bearing error from the assigned course/radial/bearing error collected by simulator with ACS has dropped to 0.39 CDI from 0.65 CDI, which is the average mean of courses/radials/bearings without the ACS. This indicates a 1.66 times improvement which is supported by a large t-value of 16.21. Hence, the fourth sub-hypothesis (H4) was supported (p<0.01), suggesting that integrating augmented cognition with automation systems in the aircraft cockpit decreases pilot errors in course/radial/bearing controls.

Table 4. Course, Radial, or Bearing Error t-Test: Paired Two Simple for Means

	Without ACS	**With ACS**
Mean error	0.65	0.39
Variance	0.02	0.02
Observations	60.00	60.00
Pearson correlation	0.58	
Hypothesized mean difference	0.00	
Df	59.00	
t stat	16.1	
P(T<=t) one-tail	0.00	
t critical one-tail	1.67	

Figure 22 shows an example of the vertical and horizontal profiles of one of the simulated flights with standard instruments and no augmentation. The red line in the top left section of the figure shows the lateral path taken by the aircraft from BWI airport to IAD airport. The waves on the red line indicate deviation from the coordinated path provided by ATC. The bottom section of the figure shows vertical positions of the aircraft throughout the flight. The steps on the line correspond to the descent and the waves show the deviation from the assigned altitude by the ATC.



Degrees: 270

Precipitation: NONE

Precipitation Rate: VERY_LIGHT

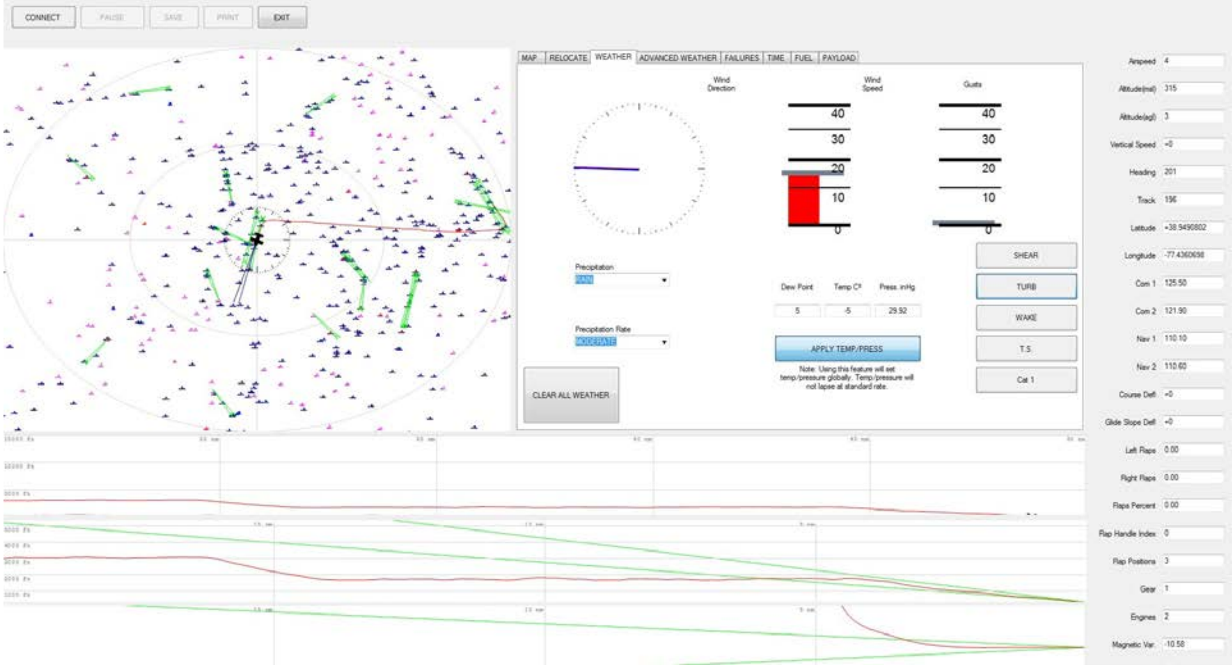
Dew Point: 5
Temp C°: -5
Press. inHg: 29.88
☐ LAPSE

Note: If 'LAPSE' is not selected 'TEMP/PRESSURE' will be set globally.

Airspeed: 4
Altitude(msl): 315
Altitude(agl): 3
Vertical Speed: +0
Heading: 203
Track: 201
Latitude: +38.9488067
Longitude: -77.4360862
Com 1: 120.40
Com 2: 125.15
Nav 1: 110.10
Nav 2: 113.80
Course Defl: -1
Glide Slope Defl: +0
Left Flaps: 1.00
Right Flaps: 1.00
Flaps Percent: 1.00
Flap Handle Index: 3
Flap Positions: 3
Gear: 1
Engines: 2
Magnetic Var.: -10.58
Ground Altitude: 312

Figure 22. Flight Precision from Simulator without ACS

Figure 23 shows an example of the vertical and horizontal profile of one of the simulated flights with standard instruments and integrated ACS. As this figure illustrates, the flight with the ACS is more precise and the lines are smoother and there are fewer waves (i.e., or deviation from ATC instructions).



Precipitation: RAIN

Precipitation Rate: MODERATE

Dew Point: 5
Temp C°: -5
Press. inHg: 29.92

Note: Using this feature will set temp/pressure globally. Temp/pressure will not lapse at standard rate.

Airspeed: 4
Altitude(msl): 315
Altitude(agl): 3
Vertical Speed: +0
Heading: 201
Track: 196
Latitude: +38.9490802
Longitude: -77.4360698
Com 1: 125.50
Com 2: 121.90
Nav 1: 110.10
Nav 2: 110.60
Course Defl: +0
Glide Slope Defl: +0
Left Flaps: 0.00
Right Flaps: 0.00
Flaps Percent: 0.00
Flap Handle Index: 0
Flap Positions: 3
Gear: 1
Engines: 2
Magnetic Var.: -10.58

Figure 23. Flight Precision from Simulator with Proposed ACS

7 Conclusion

Flight automation's main benefit is that it relieves pilots from having to focus on ordinary flight tasks, which then frees them to concentrate on overall flight performance, prepare for upcoming tasks, and respond to unexpected events. However, as human factors studies have demonstrated, pilots frequently lose their situational awareness due to loss of concentration while using automation systems (Casner & Schooler, 2014; Wise, Garland, & Hopkin, 2009). As Casner and Schooler (2014) indicate:

> *This leaves pilots to watch over the automation as it does its work, but people can only concentrate on something uneventful for so long. Humans aren't robots. We can't stare at a green light for hours at a stretch without getting tired, bored, or going crazy.*

The results of this study demonstrate that integrating an ACS into the cockpit not only enhances the pilot's ability to fly the airplane more precisely, but also increases the pilot's situational awareness by improving the human-machine interface through the human-in-the-loop concept. The ACS presented in this study creates a closed-loop system by continuously monitoring and interacting with flight systems and the pilot. By providing instructions to the pilot rather than simply automatically correcting errors and performing relevant tasks, the ACS keeps the pilot engaged at all times during the flight and increases situational awareness. In addition, the ACS reduces the pilot's workload. By systematically using the system's risk-management and decision making tools to identify the optimal corrective action or upcoming pilot tasks, the ACS prioritizes tasks and presents them to the pilot step by step.

During the simulation without ACS, 92 percent of pilots used inflight checklists and procedures only to a moderate extent. When ACS was added, 92 percent of pilots reported using them to a great extent—a significant improvement, particularly in a context in which human errors can have serious consequences. Data also show that the ACS used in the study allowed pilots to fly the airplane more precisely, with or without autopilot.

With technological advances in avionics, automation, and computing processes, there is a trend towards disengaging humans from their work. This poses the challenge of rethinking the interaction between humans and machines to create an environment that combines the best features of both to keep humans engaged in their work. In this research, we propose the use of ACS to keep pilots engaged.

Additionally the costs associated with integration of ACS with the aircraft FMS system can be assessed in future studies. For airlines, this will include both the cost of the aircraft and the cost of integrating ACS electronically with FMS in the cockpit. This integration can be done during the normal maintenance to reduce the integration cost. Our research demonstrates that significant benefits can be realized with integrating ACS.

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