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Nicholas A. Koeppen
Embry-Riddle Aeronautical University

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The Influence of Automation on Aviation

Accident and Fatality Rates: 2000-2010

Nicholas A. Koeppen

Embry-Riddle Aeronautical University

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Abstract

The purpose of this project is to evaluate if technological advances and implementation of automation have produced a decrease in the number and severity of accidents in commercial aviation over the last decade. To accomplish this evaluation historical commercial aviation accident data from 2000 to 2010 will be examined. Commercial fixed wing and rotary wing data will be evaluated. No aviation incident data will be collected; the project will be limited in scope to commercial aviation accidents. Accidents highlighting major deficiencies involving automation will be discussed in detail. To further support the projects purpose, emphasis will be given to evaluate the influence and role of pilot training in relation to automation, to pilot over-reliance on automation, to the merits of intuitive interface design, and to the role of crew coordination has played in either reducing or increasing the accident rate and severity during the specified time period.

Keywords: proposal, program outcomes, automation, accidents

Proposal

Automation: Human Error

Statement of the Project

“On December 17, 1903, at Kitty Hawk, North Carolina, the 1903 Wright Flyer became the first powered, heavier-than-air machine to achieve controlled, sustained flight with a pilot aboard” (National Air and Space Museum, n.d., para 1). During this historic flight, the pilot controlled all aspects of the Wright Flyer by utilizing a set of flight controls physically linked to controlling surfaces. “Technological advances since the early days of flight have significantly transformed the aircraft cockpit and have altered the relationships among the human pilot, the aircraft, and the environment” (Mosier, 2010, p. 147). The role of the pilot has evolved from physically manipulating flight controls and interpreting cues into a role where they “interact and control complex systems and play a central role in system safety” (Strauch, 2002, p. 13). The purpose of this project is to evaluate to what extent technological advances and implementation of automation have resulted in a decrease in numbers and severity of accidents in commercial aviation over the last decade.

In order to provide adequate data to prove or disprove the focus of this project, a detailed review of relevant literature will be conducted. This review will be conducted focusing on two primary areas. The first focus area will consist of a review of relevant literature highlighting human error, or human factors in relation to automation technology. Attention during the review will be given to defining automation, discussing optimal automation levels, analyzing benefits versus shortcomings of automation, and establishing trends in causal factors related to automation technology accidents. The second area will consist of a review of commercial aviation accident data covering a time period from 2000 through 2010. The year 2000 will be used as a base for

comparison and provide data for an entire year prior to 2001 when commercial aviation traffic was severely affected by the events of September 11. The use of the year 2000 as a base for comparison will help identify any statistical irregularities directly caused by changes in commercial air traffic during 2001 and the years following. Specific accidents will be sighted as necessary to support findings and recommendations.

As part of the review of relevant literature, past studies of accident statistics dealing with automation technology will be analyzed and used to draw inferences and distinctions when compared to the accident data collected for the period of 2000 to 2010. Further analysis will be given to evaluating pilot training in relation to automation, to pilot over-reliance on automation, to the merits of intuitive interface design, and to the role of crew coordination in relation to varying levels of automation technology.

This project will analyze both fatal and nonfatal commercial aviation accidents relating to automation technology. Aviation incidents and data pertaining to near accidents involving automation technology will not be analyzed as part of this project. Data collection will be limited to U.S. based commercial air carriers, but will include accidents occurring domestically, international carriers included and of U.S. based commercial carriers involved in accidents abroad.

Recommendations will be based on results of accident data analysis, and related to human factors issues or trends that are identified during the literature review and data collection. Recommendations are expected to be focused on improvements in system engineering, system testing, crew or operator training, and the continuous attempt to engineer error out of systems.

Program Outcomes

PO #1

Students will be able to apply the fundamentals of air transportation as part of a global, multimodal transportation system, including the technological, social, environmental, and political aspects of the system to examine, compare, analyze and recommend conclusion.

The **global, multimodal** transportation system aspect will be addressed when discussing the benefits of automation technology across commercial aviation. For example, “by reducing workload, automation can also raise the productivity of each operator, decreasing the number of operators needed and lowering operating costs” (Strauch, 2002, p. 221). The **technological** component will be addressed when evaluating the argument, “technological advances reduce the role of human operator, thereby leading to a reduction in operator errors or reduced consequences from operator errors” (Strauch, 2002, p. 220). **Social, environmental, and political** aspects will be covered while evaluating the influences of a reduction in severity and occurrences of aviation accidents in commercial aviation.

PO #2.

The student will be able to identify and apply appropriate statistical analysis, to include techniques in data collection, review, critique, interpretation and inference in the aviation and aerospace industry.

The **statistical analysis** aspect will be met by performing data collection and analysis of historical commercial aviation accident data ranging from 2001 to 2011. Histograms will be constructed to display accident **data collected** for each year in question. Differences in casual factors and severity will be highlighted. Comparisons will be provided regarding automation detailing size of aircraft fleets compared to accidents numbers, number and severity of accidents,

as well as a comparison between nonfatal and fatal accidents and rates. An ANOVA is a “hypothesis-testing procedure for studies with three or more groups” (Aron, Coups, & Aron, 2011, p. 463). An ANOVA will be utilized to **review, critique, interpretate**, and draw **inferences** about the data collected.

PO #3

The student will be able across all subjects to use the fundamentals of human factors in all aspects of the aviation and aerospace industry, including unsafe acts, attitudes, errors, human behavior, and human limitations as they relate to the aviators adaption to the aviation environment to reach conclusions.

Human factors play a role in all aspects of aviation. Thanks to automation, that role is now “performed at a higher cognitive and a lower physical level than was true of operators who manually controlled the machines” (Strauch, 2002, p. 13). The review of historical commercial accident data and specific accidents will establish trends in causal factors related to automation technology. More specifically, pilot training, over-reliance on automation, intuitive interface design, and the role of crew coordination will be examined in an effort to identify **unsafe acts** or **human behaviors** conducive to committing errors involving automation.

Errors and **human limitations** will be evaluated dealing with automation system designs. “Systems that people design, manage, and operate, cannot be immune to error because of the inherent imperfections of the human designer and operator” (Strauch, 2002, p. 25). Human **attitudes** and **behaviors** will be discussed in regard to the role pilots now play as system monitors or facilitares in commercial aviation. Automation has caused an evolution in aviation on the job duties of the pilot and attitudes and behaviors are vital for the safe operation of automation technology.

P0#4

The student will be able to develop and/or apply current aviation and industry related research methods, including problem identification, hypothesis formulation, and interpretation of findings to present as solutions in the investigation of an aviation/aerospace related topic.

The **problem identification** component will be demonstrated by providing examples of pilot over reliance on automation, substandard training in relation to automation technologies, breakdowns in crew coordination, and latent automation system errors. These Latent errors, “whose adverse consequences may lie dormant within the system for a long time” (Reason, 1990, p. 173), and only become obvious when other factors bring them to the surface.

Hypothesis formulation and interpretation of findings are vital aspects of proving or disproving research. “A hypothesis is a logical supposition, a reasonable guess, and educated conjecture” (Leedy & Ormrod, 2010, p. 4). This study will be focused around the following hypothesis: There has been a statistical decrease in the number and severity of commercial aviation accidents involving automation from 2000 to 2010. Furthermore the decrease can be attributed to the evolution of pilot training in regard to automation, a decrease in over-reliance on automation, advances in intuitive interface design, and improvements in training and utilization of crew coordination.

PO #5

*The student will investigate, compare, contrast, analyze and form conclusions to current aviation, aerospace, and industry related topics in aeronautics, including **advanced aerodynamics, advanced aircraft performance, simulation systems, crew resource management, advanced meteorology, rotorcraft operations and advanced aircraft/spacecraft systems.***

In order to meet the requirements of this program outcome I will address the aspects corresponding to the classes I have completed. The classes include: Rotorcraft Operations, Advanced Meteorology, Aviation/Aerospace Simulation Systems, and Advanced Aerodynamics.

A discussion of **advanced aerodynamics** will be utilized to provide an understanding of considerable aerodynamic events caused by automation or errors utilizing automation technology. In keeping with the scope of this study, the aerodynamic events themselves will not necessarily be the primary focus, but understanding the nature of the event is vital to understand the relationship between automation and certain accidents.

Simulation systems provide an economical and safe environment to train, evaluate, and study a multitude of events from emergency procedures to basic glass cockpit operation. The role **simulation systems** play in pilot training in relation to automation, testing of automation and intuitive design, and the evolution and training of crew coordination will be thoroughly discussed. The use of simulation in the initial design and testing phases of automation technology will also be investigated.

Rotorcraft operations and **advanced meteorology** will also be discussed as part of this program objective. **Rotorcraft operations** will be discussed as part of the accident investigation data, and commercial rotorcraft accidents will be compared to commercial fixed wing accident data. **Advanced Meteorology** will be discussed when in relation to any commercial accidents where weather played a role in accident that relates to automation.

PO #9

*The student will investigate, compare, contrast, analyze and form conclusions to current aviation, aerospace, and industry related topics in safety systems, including **systems safety**,*

industrial safety, accident investigation and analysis, transportation security, airport safety and certification, safety program management, and aviation psychology.

In order to meet the requirements of this program outcome I will address the aspects corresponding to the classes I have completed. The classes include: Aviation/Aerospace Industrial Safety Management, Aviation/Aerospace Psychology, Aviation/Aerospace Accident Investigation and Analysis, and Aviation/Aerospace System Safety.

“The increased role of automation in systems has enhanced many aspects of system operations, but it has also led to unique antecedents to errors, errors that have led to incidents and accidents” (Strauch, 2002, p. 217). **System safety** will be discussed in detail during the evaluation of intuitive interface design, automation system engineering practices, the implementation of automation technology designed for commercial aviation, and system safety failures highlighted during **accident investigations**. The complexity of current and emerging next generation technology will also be addressed from a **system safety** standpoint.

The important role of **aviation psychology** in automation technology design, training, implementation, and **accident investigation** will be addressed. Of particular interest are various theories of error and how they are used in engineering efforts to reach the optimal automation level within a system. “Modern error theory suggests that in complex systems, operator errors are the logical consequences of antecedents or precursors that had been present in the systems at the time they were committed” (Strauch, 2002, p. 16). Theories presented by error theorists Freud, Norman, Rasussen, and Reason will be discussed in detail during this program outcome.

Industrial safety’s role in this program outcome will not be as extensive as system safety, aviation psychology, or accident investigation. However, it will provide a worthwhile example of how automation technology is not limited to airborne operations in commercial

aviation. Ground operations at airports worldwide provide a wide variety of automated industrial safety systems and they are evolving at a staggering rate.

Accident investigation data will make up a large portion of this study. Data will be collected for commercial aviation accidents dating from 2000 to 2010. Effort will be focused on providing there has been a decrease in the significance and number of accidents relating to automation over the afore mentioned years. Significant accidents will be discussed in detail to support theory, “that the consequences of even “minor” will present a threat to the safety of complex systems” (Strauch, 2002, p. 16).

The Influence of Automation on Aviation Accident and Fatality Rates: 2000-2010**Project Introduction**

To be the first is something of a rarity, especially in today's age where a truly new invention is something that does not come around but once in a lifetime. The concept of flight was the stuff of fairy tales until the Wright Brothers introduced it to the world, and the notion of a pilot was no different. The Wright Brothers designed their craft to give the pilot full control, but advances in automation changed the role of a pilot from dreamer, designer, constructor, fixer, and fact gatherer – in other words, the be all and end all of flight – to less of a controller and more of a systems observer. Regardless of the myriad changes introduced by automation, the role of the pilot is still crucial; throughout early aviation history, some of the most groundbreaking aeronautical advancements were fueled from start to finish by the person who flew/tested aircraft.

With the passage of time, the passion that once fueled the development of the aviation industry has subsided and the pilot's role has forever evolved. From an early all-encompassing role, to a role that saw pilots perceived as "daredevils" of the sky, to the current view of a pilot as a working professional – all of this change has been precipitated by technology and has transformed flying from a task of complete aircraft control by the pilot to one of task supervision and system monitoring. This kind of change is not without consequence. As technology continues to redefine the piloting role, pilots themselves have adjusted, but not without error. To err is human, but the role between automation and human error is one to be explored; human factor errors have emerged as the number one contributing factor in commercial aviation accidents.

This study will explore the relationship between commercial aviation accidents, fatalities, and automation and will be presented in the following order: (1) Definition of relevant terms; (2) Literature review; (3) Methodology; (4) Results; (5) Conclusion; and (6) Recommendations for future research.

A comprehensive literature review was conducted to establish a knowledge base in subject areas relevant to the aviation industry. This review focuses on the following topics, but is not limited to: defining automation, outlining the history of automation in aviation, discussing optimal automation levels, analyzing the benefits versus shortcomings of automation, defining the subcategories that comprise human factors analysis, and discussing the role played by automation in preventing or causing aviation accidents and/or fatalities.

The literature review serves two purposes for this study. First, it makes an attempt to define the terms relevant to human factor analysis within the aviation and aerospace industry. Second, it serves to inform the theoretical underpinnings of automation technology in relation to human factor errors and how they relate to the aviator's adaptation to the aviation environment, and how automation may or may not have affected aviation outcomes, especially in relation to part 121 and part 135 aviation accidents and/or fatalities.

In defining relevant terms, the literature review plays a valuable role in describing the various models of accident causation, especially related to the very broad human errors factor. A review of the literature revealed the widely accepted and utilized Human Factors Analysis and Classification System (HFACS); the qualitative analysis section of this study will define this classification system and discuss how this study used the HFACS as a basis to classify probable causes of aviation accidents/fatalities.

The literature review also plays a crucial role in aiding the determination of variables to be included in the statistical models. From relevant literature, this study draws the most important explanations and findings and uses them as inputs into the choice of variables (causes and indicators) in the empirical models. This allows the elaboration of statistical models that include all relevant indicators, thus lessening the likelihood that the models suffer from limitations caused by omitted or irrelevant variables. The literature review also helps inform hypotheses regarding the expected direction of the statistical relationship between the independent and dependent variables.

This study's hypothesis is as follows: There has been a statistical decrease in the number and severity of commercial aviation accidents involving automation from 2000 to 2010. In addition to attempting to prove or disprove the hypothesis, an attempt will be made to attribute the hypothesized decrease in aviation accidents and severity to the evolution of pilot training in regard to automation, a decrease in over-reliance on automation, advances in intuitive interface design, and improvements in training and utilization of crew coordination.

To accomplish the aforementioned, a series of statistical analyses were developed and executed based on the findings of the review of relevant literature. The methodology section of this study will follow the review of relevant literature and discuss data gathering, constraints to analysis, development of the statistical models, and limitations of this study.

Definitions

Part 121 and Part 135 Operations. Part 121 and Part 135 operations are defined as follows:

In the United States, civil aviation is regulated by the U.S. Federal Aviation Administration (FAA), and a broad distinction is made between commercial air carrier

operations and general aviation operations. Air carriers are defined as operators that fly aircraft in revenue service, and operators are regulated by Title 14 *Code of Federal Regulations* (CFR) Parts 121 and 135. Part 121 usually refers to operators who fly large transport-category aircraft in controlled airspace and controlled airports that have available specific weather, navigational, operational, and maintenance support. Part 135 regulates commercial air carriers flying smaller aircraft with nine or fewer passenger seats, often into smaller airports that do not provide the services required to support Part 121 operations. Air carrier operations under either Part 121 or Part 135 may be scheduled, meaning that the operator offers, in advance, the departure location, departure time, and arrival location. Operations may alternatively be non-scheduled or on-demand, meaning that the departure location, departure time, and arrival location are negotiated with the customer. Non-scheduled Part 121 operations include cargo flights and certain charter flights in transport-category aircraft, whereas on-demand Part 135 operations include charter, air-taxi, and certain medical transport operations. (National Transportation Safety Board, 2011, pp. 4-5).

Aircraft Accident. The Department of Transportation (DOT) defines an aircraft accident as:

An occurrence associated with the operation of an aircraft that takes place between the time any person boards the aircraft with the intention of flight and all such persons have disembarked, and in which any person suffers death or serious injury, or in which the aircraft receives substantial damage. For purposes of this part, the definition of “aircraft accident” includes “unmanned aircraft accident. (2012, para. 2)

Incident. The DOT defines an aircraft incident as “an occurrence other than an accident, associated with the operation of an aircraft, which affects or could affect the safety of operations” (2012, para. 5).

Fatality. A fatal injury is defined as “any injury which results in death within 30 days of the accident” (Department of Transportation, 2012, para. 4).

Serious Injury. The DOT defines a serious injury as:

Serious injury means any injury which: (1) Requires hospitalization for more than 48 hours, commencing within 7 days from the date of the injury was received; (2) results in a fracture of any bone (except simple fractures of fingers, toes, or nose); (3) causes severe hemorrhages, nerve, muscle, or tendon damage; (4) involves any internal organ; or (5) involves second- or third-degree burns, or any burns affecting more than 5 percent of the body surface. (2012, para. 8)

Review of Relevant Literature

Automation

Automation is the primary focus of this study, especially the influence it exerts on all aspects of aviation, from the effects it has on human factors to the role it plays in potentially contributing to or preventing aviation accidents and/or fatalities. This section will define automation, present a brief history of the topic, and discuss the various levels of automation.

Automation Defined

The history of automation, which is not exclusive to the aviation industry, is extensive and dates back over 200 years. The term itself implies automatic control, and has been used in a variety of ways throughout the history of automation. Automation is defined by the Merriam-Webster dictionary as: (1) the technique of making an apparatus, a process, or a system operate

automatically; (2) the state of being operated automatically; or (3) automatically controlled operation of an apparatus, process or system by mechanical or electronic devices that take the place of human labor (2012). To provide evidence of the diverse uses of the term, which are often based on the process being described, multiple definitions will be discussed in more detail below.

Mouloua, Hancock, Jones & Vincenzi (2010) define automation as the execution of a task, function, service or subtask by a machine agent (p. 8-2). This definition is more succinct using the reference to a machine agent to describe any mechanical or electronic execution of a task, function, service, or subtask. This execution can be in an open loop or closed loop system, it can imply a variety of types of controls or actions, and it can refer to anything from a basic level of automation to a fully automated system. The second definition does not make mention of a human's task execution being replaced by a machine agent, but it is assumed.

Billings (1991) defines automation as a system or method in which many of the processes of production are automatically performed or controlled by self-operating machines, electronic devices, etc. (p. 7). Although processes are automatically performed in these systems, it is important to note they do not operate completely autonomously. In aviation, pilots are still at the center of operation of any aviation automation system and are required for safe operation.

Billings further defines human-centered automation as automation designed to work cooperatively with human operators in the pursuit of stated objectives (p. 7). Expanding on the definition of human-centered automation, automation is considered a tool or resource. It is used to accomplish a task that otherwise would be impossible for a human to accomplish or to facilitate the accomplishment of a task with greater efficiency. It is also considered a means to

reduce attention or workload from operators, but does not preclude the need for a human operator for management and direction of the system (Billings, 1991, p. 7).

At the center of any form of automation, an unmistakable human-machine relationship will exist. First, in order for automation to occur, a form of human labor is automated in some way. Second, any automated system requires a human operator or monitor to function properly. Because of this dependent relationship, Parasuraman, Sheridan & Wickens (2000) define automation as a device or system that accomplishes (partially or fully) a function that was previously, or conceivably could be, carried out (partially or fully) by a human operator (p. 287). Because the human-machine comparison described in the last definition is the most appropriate to the theme of this study, it will be used as the standard definition when referring to automation throughout the remainder of this study.

“In aviation, automation most often refers to the autopilot, flight management system (FMS), as well as other burgeoning advanced cockpit-related systems and functions” (Mouloua, Hancock, Jones & Vincenzi, 2010, p. 8-2). These systems have forever altered the role of the pilot and will continue to become more complex. The history of aviation automation is relatively short, but was spurred by other technological advances and its use will continue to grow with the complexity and performance of the systems themselves.

Brief History of Automation

Leather jackets, white scarves, and flying by the seat of your pants are things of the past, phased out during the evolution of automation technology. The allure of aviation as an adventurous and daring career has fallen by the wayside as a result of advances in automation technology; it has since been replaced by a career filled with computer programming and monitoring. The history of automation is extensive and reaches far back before the birth of

aviation. Long before the need to reduce pilot workload, history saw the advent of simple machines that improved the accuracy and speed of manual tasks.

One of the first such machines, and perhaps the most famous because of the controversy it created, was the automated weaving loom. Created by Joseph Marie Jacquard in 1801, the automated loom threatened the lifestyle and livelihood of men and women who spent years developing their professional skills. Confronted by this new automation technology, which was more precise and efficient, fear and frustration grew over the next decade. In 1811, violent riots occurred in Nottingham and Lancashire, England resulting in the destruction of mills and machinery. The British government eventually quelled the protesters, called “Luddites,” but they left their mark on history. Fourteen protestors were hanged in 1813, and the name “Luddite” became synonymous with someone who will not accept technological change (Manningham, 1997, p. 56).

After the invention of the automated weaving loom, “cotton gins and combines, automobiles and railroads, computers and robots have changed the workplace forever” (Manningham, 1997, p. 56). However, nowhere is the need for automation more evident than in aviation. “Not all of the functions required for mission accomplishment in today’s complex aircraft are within the capabilities of the unaided human operator” (Billings, 1991, p. 8). Prior to the technological advances of present-day aviation, the need for aviation automation was identified – even before the first powered flight.

“In the early days of aviation, the pilot set forth unaided, with only human perceptual capabilities to provide necessary information” (Billings, 1991, p. 8). The machines they flew were recognized by their designers as unstable, thus tremendous efforts were made toward designing tools and/or systems that would provide pilots with needed assistance. As early as

1905, Orville Wright started working on a stability augmentation device. “The device, complete and ready for testing by the fall of 1913, was designed to keep an airplane flying straight and level without the intervention of the pilot” (Crouch, 1989, p. 459). Wright was awarded the prestigious Collier Trophy in early 1914 for a demonstration of hands-off flight, but it was later that year a revolution occurred in automation technology. Lawrence Sperry developed a two-gyroscope system that would sense deviations from straight and normal flight and apply appropriate corrections. “The enormously complex inertial navigation system that guided the first men to the Moon in 1969 was directly rooted in Sperry’s automatic pilot of 1914” (Crouch, 1989, p. 460). Stability augmentation devices continued to advance and by the 1930s autopilots for long distance flying were considered essential (Billings, 1991, p. 8).

Aviation automation has flourished over the years with the introduction of new aircraft capabilities and technological advances. Retractable landing gear prompted the requirement for a landing gear configuration warning system. The invention of four-engine aircraft drove the development of the automatic propeller synchronizing system. This drive was similar to that which caused propeller-feathering devices to be produced to help control World War II airplanes, which were unstable if an engine failed on takeoff. Advances in electronic technology combined automatic navigation with stability augmentation and further advanced the autopilot (Billings, 1991, p. 8).

“The average transport aircraft in the mid-1970s had more than 100 hundred cockpit instruments and controls, and the primary flight instruments were already crowded with indicators, crossbars, and symbols, and the growing number of cockpit elements were competing for cockpit space and pilot attention” (Chambers, 2010, para. 5). Advances in digital systems coupled with the increasing amount of air traffic and system complexity spurred the need to

improve cockpit functionality and design. “Electronic flight displays were first developed for military applications in the 1960s, and by the 1970s, computer-driven cathode ray tubes (CRT) displays began replacing electromechanical instruments in commercial transport-category airplanes” (National Transportation Safety Board, 2010, p. 4). The use of integrated displays in the 1970s allowed the merging of aircraft status, position, and control information into displays, which saved space. Developed in conjunction with early forms of aircraft automation, the goal of these displays was to reduce crew workload and improve safety (National Transportation Safety Board, 2010, p. 4).

With the integration of glass cockpits and automation systems, questions began to arise as to the validity and reliability in conjunction with human factors error analysis. The NASA Ames Research Center received a mandate to evaluate safety implications and human factors in reference to technological advances in cockpit technology. The research was conducted utilizing displays capable of processing flight and aircraft system data, interpreting it, and presenting it in a clearly understandable manner. In 1979, “the success of the NASA-led glass cockpit work is reflected in the total acceptance of electronic flight displays” (Chambers, 2010, para. 6).

Display technology and automation continued to improve. Following every advance in display technology, advancements in flight management and automation systems were evident. “In 1981 the Presidential Task Force on Aircraft Crew Complement recommended that transport aircraft could be safely flown by a two-pilot crew” (Wiener, 1989, p. 2). The significance of the Presidential Task Force’s findings allowed manufacturers to design, produce, and retrofit commercial aircraft focused on two flight crewmembers. The report also validated a previous certification performed by the Federal Aviation Administration (FAA) in regards to the DC-9-80 as a two-pilot aircraft. The report also ushered in “a new era of economical trans-oceanic

operations for two-engine, (generally) two-pilot glass cockpit aircraft” (Chute, Wiener, & Moses, 1999, p. I-6). The monetary savings automation integration provided to design and operations were of great significance to the airlines following the implementation of the Presidential Task Force’s findings (Wiener, 1989, pp. 1-2).

Following the turn of the century and through present day, the widespread development and use of automation continues to grow. Various levels of automation are considered standard in commercial airlines and military aircraft, and are continuing to transition to general aviation. Flight and performance management systems, as well as automated flight control and navigation systems, were made possible with the introduction of digital computers and advances in automation technologies. These technological advances will continue to fuel further developments and the advent of greater levels of automation.

Levels of Automation

“Through the auspices of the technological imperative, automation has steadily advanced as means have been found for automating physical, perceptual, and, more recently, cognitive tasks in all kinds of systems” (Endsley, 1996, p. 163). It is obvious that there are many benefits to automation, however none more important than trying to determine the optimal level of automation. This section will explore a basic four-stage model of human information processing, which will assist in selecting the appropriate level of automation among the 10 levels defined by this four-stage model.

Establishing requirements of interaction and processing from a human user perspective is crucial to operate and make decisions, or simply put, to define the need for interaction with an automated system. Four generic functions are outlined by Endsley (1997) that are intrinsic to many industries, including aviation, and make it possible to evaluate optimal automation and

human interaction needs. The functions are: (1) monitoring/scanning displays to perceive system status, (2) generating/formulating options or strategies for achieving goals, (3) selecting/deciding on a particular option or strategy, and (4) implementing/carrying out the chosen option.

The first function can be simplified as sensory processing, and refers to the acquisition and processing of various sources of data. This function includes position and orientation of sensory receptors, and pre-processing and processing of sensory data. The second function deals with perception and working memory. This stage involves using working memory to retrieve and manipulate processed information. Decision-making is the next function and uses a cognitive process to evaluate all previously gathered information to make informed choices regarding the information supplied. The last function can be simplified as response selection. This function involves implementing the decision in the form of a response or action (Parasuraman, Sheridan, & Wickens, 2000, p. 287).

The 10 levels of automation contain varying roles of the human operator and automated controls dependent on the level. They range from full manual control to fully automated control. Level one, which is the lowest level of automation, requires the human operator to make all decisions and initiate actions with no assistance provided by a computer. The second level, or action support level, offers a complete set of decisions or actions to be selected or initiated by the human operator. Level three narrows the selections for system operations, and although the human operator may select the operation, the computer implements actions. Level four is known as the shared level and presents the human operator with one alternative to operation and sees a sharing of all tasks except for selection. Level five is known as decision support. This level offers suggestions and implements those selections only if the human operator approves. The next level is referred to as the blended decision making level, and allows a predetermined time to

select an alternative action before the computer will execute. Level seven is rigid, with a computer executing required tasks and informing the human monitor. Level eight, also referred to as automated decision-making, informs the human operator if information is requested. Automation level nine once again goes a step closer to being fully automated by only informing the human monitor of actions if it decides to. In the highest level of automation, the computer decides everything, acts autonomously, and ignores the human operator/monitor (Parasuraman, Sheridan & Wickens, 2000, p. 287).

Finding the right level of automation for aviation systems is an extremely daunting task, and one to which extensive research has been dedicated. Proposed automation levels need to be carefully tested to determine if they are reliable, provide adequate feedback, and are appropriate for the task or situation for which they were developed.

Problems with Automation

Because of the advent of automation, “designers have argued that technological advances reduce the role of the human operator, thereby leading to a reduction in operator errors or reduced consequences from operator errors” (Strauch, 2004, p. 220). There is no doubt automation has improved many aspects of operator performance. “It leads to superior productivity, efficiency, and quality control” (Norman, 1989, p. 4). However, for these benefits to be realized, many problems or shortcomings to automation must be overcome. This section will discuss six prominent problems with automation in aviation systems. These issues are widely recognized as drawbacks of automation and they include increased monitoring and vigilance requirements, loss of pilot skills, inappropriate feedback and user interface, workload redistribution, over-reliance on automation and mistrust, and lack of familiarization with systems.

As previously discussed, automation has redefined the pilot's role from directly and manually controlling all aspects of flight to less of a direct operator and more of a system monitor. Levels of monitoring/manual control are dependent upon the level of advanced technology available in various aircraft. The fewer manual tasks a pilot has to perform, the more automated systems and subsystems they are required to monitor. Automation can also remove or distance the monitor from system cues that are required to make informed decisions involving automated systems. Automated systems may also provide information that does not correctly convey system operation or status, which can diminish a monitor's mode awareness.

“Researchers have obtained considerable evidence demonstrating that increasing automation and decreasing operator involvement in a system control reduces operator ability to maintain awareness of the system and its operating states” (Strauch, 2004, p. 224). Humans do not make good system monitors, and when asked to perform manual tasks in conjunction with monitoring automated subsystems, their performance decreases (Strauch, 2004, p. 224). Furthermore, long-term participation as a system monitor rather than as an active controller can also lead to reduction in baseline skill levels, weaker internal models of system processes, and reduced decision-making abilities, particularly for highly automated system functions (Kantowitz & Campbell, 1996, p. 125).

Automating tasks essentially removes the pilot from executing key system functions and operations. “This out-of-loop time may reduce the pilot's skills to the point that he or she is no longer effective in a system emergency or failure” (Kantowitz & Campbell, 1996, p. 125). This can be perpetuated when “the “distance” between the operator and the system under control increases, and workload can be increased if the operator is suddenly required to jump back into the active control loop and directly control the system” (Kantowitz & Campbell, 1996, p. 125).

From initial flight training, pilots are instructed on how to manipulate the flight controls to achieve a desired response. With the incorporation of automation they are taught how to receive a desired response by interacting with various automated systems. Automation studies have found that pilots, “despite initial manual training, those subjects who had been operating as supervisory controllers of automation in a simulated process control task were slower and more inefficient in bringing the system under control than were subjects who had operated only in a manual mode” (Endsley & Kiris, 1995, p. 381).

Inappropriate feedback or user interface can be catastrophic in automated systems. Complex system interfaces and the way information is presented within complex systems can actually increase workloads for pilots. Eliminating visual and tactical cues can also lead to elevated workloads. Also consider, “when automatic devices compensate for problems silently and efficiently, the crew is ‘out of the loop,’ so that when failure of the compensatory equipment finally occurs, they are not in any position to respond immediately and appropriately” (Norman, 1989, p. 5). Proper feedback for a system monitor is essential for successful automation; it may not be evident during normal operational conditions but will be evident when portions of a system fail or an emergency occurs.

Workload redistribution is also a large challenge facing future automation. When tasks or systems are easy to automate, they are automated, but historically when processes are not easy to automate they are not automated. These processes usually correspond to the difficulty of the task for a manual operator to perform as well. Therefore, historically, routine tasks for operators are automated and tasks requiring a high workload effort are not automated. This type of automation has been called “clumsy,” and actually can increase rather than decrease chances for operator

errors. Maintaining vigilance when an operator's workload is excessively reduced is difficult and can lead to boredom (Strauch, 2004, p. 225).

Over-reliance on automation and mistrust are also both major concerns regarding the use of automation in aviation. "Different people may be susceptible to different types of inappropriate automation use behaviors based on their self-confidence in doing the task, their level of trust in the automation, their responses to fatigue, and their incorporation of these and other factors into their decision-making processes" (Riley, 1996, p. 34). There is a definite correlation between mistrust and over-reliance on automation. In general, an individual who is over-reliant on automation will more than likely trust the performance of that operation. The inverse could occur; however, in the case of an individual mistrusting automation to the extent that the trust in his or her own capabilities outweighs their trust in automated systems. Over-reliance on automation can lead to errors of omission, decreases in vigilance, disregard for system parameters, and an out-of-loop experience initiated by the operator/monitor. On the opposite end of the spectrum, mistrust can lead to operators choosing not to use automated systems and increasing their workload or becoming fixated on monitoring automated systems and disregard manual cues.

Lack of familiarity with automation technology can manifest itself in a variety of ways. Modern day automation systems are extremely complex and understanding automation logic continuously proves to be difficult. Common practice is to attain formal instruction and experience in becoming proficient at operating automated systems, but disregard the in-depth understanding of how and why tasks are accomplished within the automated system. This in itself usually does not present a problem if automated systems function normally, however if an anomaly is present the operator may be unaware or not possess the system knowledge to react

appropriately or address the problem. Additionally, the change in a pilot's role to that of a monitor may so "remove the pilot from the active control loop that the pilot loses familiarity with the key system elements and processes for which he or she is responsible" (Kantowitz & Campbell, 1996, p. 125). "In addition, some more sophisticated automation systems have multiple operating modes that can be initiated by each other, and require in-depth knowledge of function and logic to operate safely" (Strauch, 2004, pp. 222-223).

Human Factors

A discussion of human error is not complete without mentioning the associated theory and classification systems. The best-known and comprehensive theory to discuss both latent and active human factors is that of James Reason – the Cumulative Effect Theory, also known as the Swiss Cheese theory of accident causation. Reason is the first to move beyond focusing on active human errors – those whose effects are felt immediately – to latent errors, which may lie dormant within the system for some time, and may only become evident when they combine with other factors to breach the system's defenses. It is this focus on latent errors that is so critical in this day and age of moving beyond attributing accident causation simply to the most immediate and obvious cause, usually some type of pilot error. As Reason himself notes, it is these latent errors that "pose the greatest threat to the safety of a complex system" (Reason, 1990, p. 173).

Reason's Swiss Cheese theory details the critical mistakes that lead up to an accident and is categorized into four levels of human failure. Each level influences one another and starts with the incident and works backward. Thus the Swiss cheese analogy – the holes in the cheese represent the failures stacked one upon another.

Figure 1 details the four levels of human failure as outlined by the Swiss Cheese theory:

(1) Unsafe acts – usually referred to as pilot or aircrew error; (2) Preconditions for unsafe acts – describes any and all existing conditions prior to the accident, including but not limited to fatigue, poor communication, failures in coordination procedures or failures associated with crew resource management; (3) Unsafe supervision – could range from poor training programs, poor asset management or poor crew management; and (4) Organizational influences – may include budget, lack of training, and lack of experience, among others.

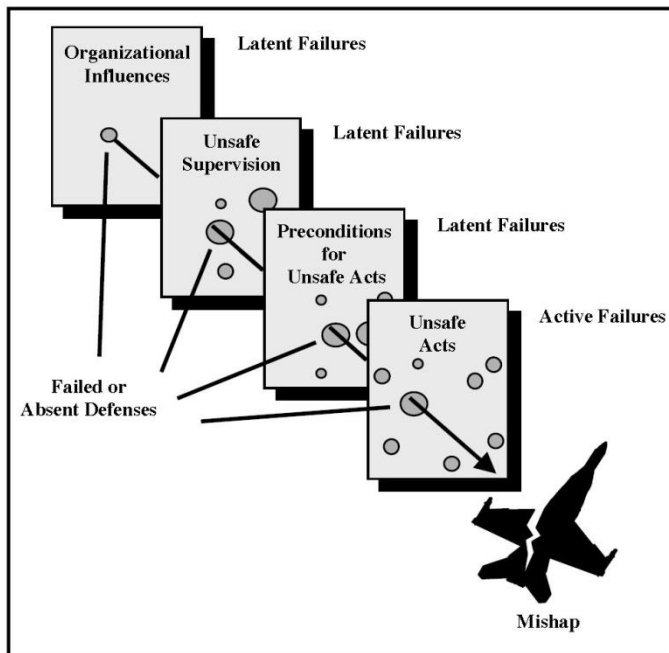


Figure 1
Reason's Swiss Cheese Model for Accident Causation (Shappell & Wiegmann, 2000, p. 2)

“The Human Factors Analysis Classification System (HFACS) is a general human error framework originally developed and tested by the U.S. military as a tool for investigating and analyzing the human causes of aviation accidents” (Weigmann & Shappell, 2001, p. 1). It permits the analysis of relationships between causal factors, further allowing the accurate, standardized, and comprehensive classification of commercial aviation data. In essence, the

HFACS takes the theory behind the Swiss Cheese accident causation model and puts it into practical application to assign probable causes to aviation accidents.

Figure 2 shows the first of four theoretical models upon which the HFACS is based, classifying unsafe acts into two categories: errors and violations. To further distinguish between errors and violations, subcategories were created for each, to include three error types (decision, skill-based, and perceptual errors) and two types of violations (routine, and exceptional) (Shappell & Wiegmann, 2000, p. 3).

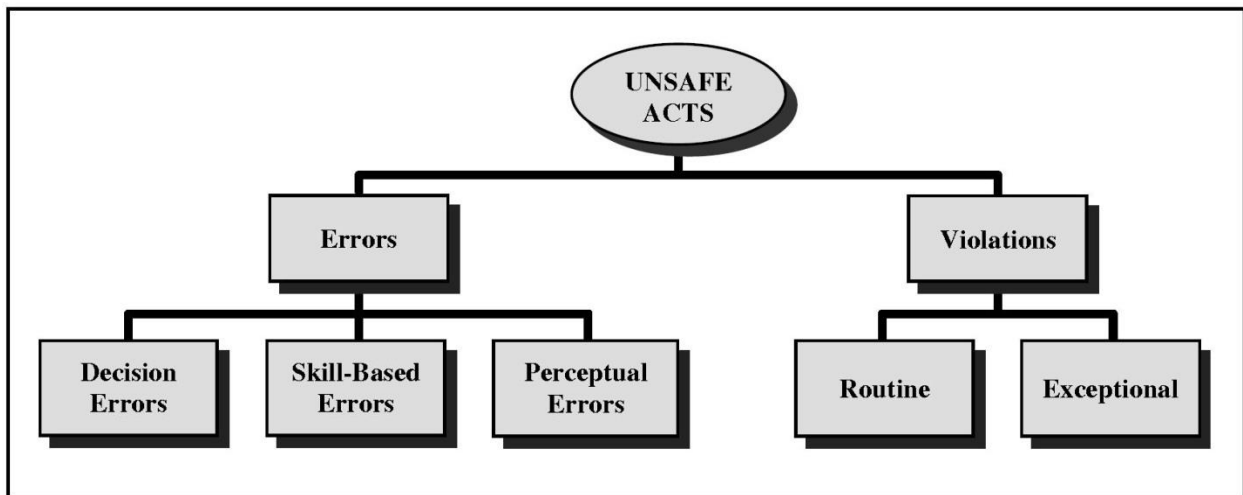


Figure 2
HFACS – Categories of unsafe acts committed by aircrews (Shappell & Wiegmann, 2000, p. 3)

The second theoretical model entitled preconditions for unsafe acts is displayed in figure 3. “Arguably, the unsafe acts of pilots can be directly linked to nearly 80% of all aviation accidents” (Shappell & Wiegmann, 2000, p. 6). Despite this overwhelming statistic, simply attributing accidents to the unsafe acts does not identify the latent failures present that allow the unsafe acts to occur. To better define the preconditions for unsafe acts, two sub-categories exist to differentiate between substandard conditions and practices of the operator.

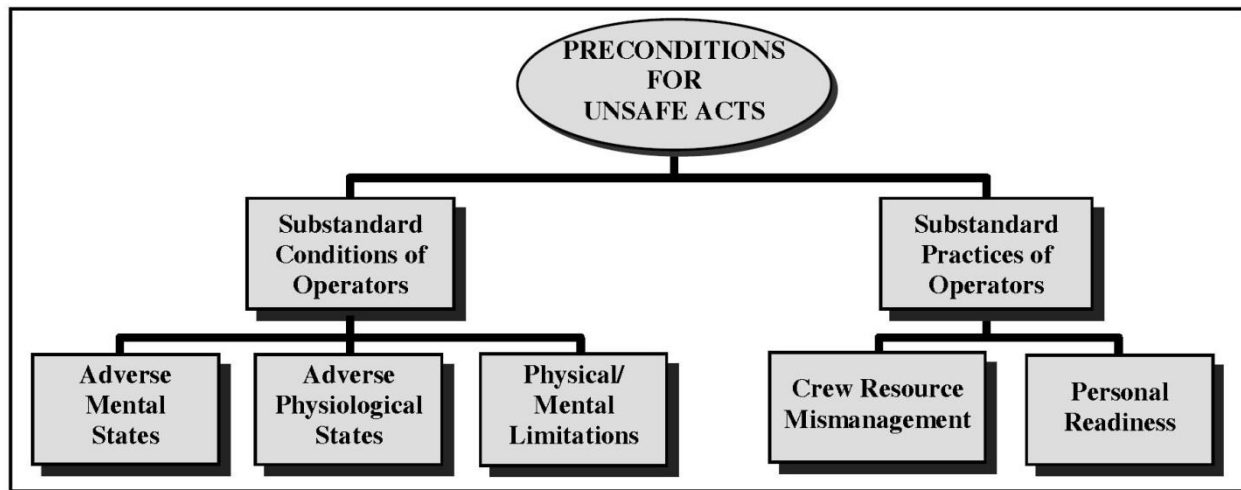


Figure 3

HFACS – Preconditions for unsafe acts (Shappell & Wiegmann, 2000, p. 6)

Reason (1990) linked causal factors associated with pilot error back to errors made in the supervisory chain. Hence, Shappell and Wiegmann (2000) identified four categories of unsafe supervision. The categories include inadequate supervision, planned inappropriate operations, failure to correct problem, and supervisory violations (Figure 4). Inadequate supervision includes errors, such as failure to provide guidance, operational doctrine, oversight, training, or track performance. The second category, planned inappropriate operations, covers errors related to a failure to provide correct data, adequate briefs, improper manning or inadequate opportunities for crew rest. Failures to correct a known problem is the third category and covers causal factors, such as failures to correct erroneous documents, initiate corrective actions, report unsafe tendencies, or identify at-risk aviators. The fourth category involves supervisory violations regarding failures to enforce rules and regulations, the authorization of unnecessary hazards or authorization of unqualified crews for flight (Shappell & Wiegmann, 2000, pp. 9-10).

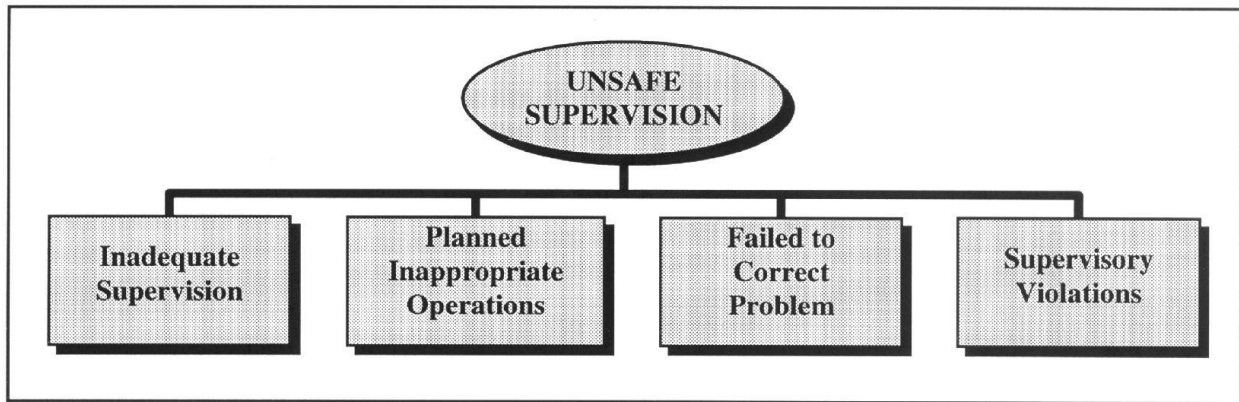


Figure 4

HFACS – Categories of unsafe supervision (Shappell & Wiegmann, 2000, p. 9)

The last of the four levels of failure within HFACS is organizational influences. As with each of the levels previously discussed, organizational influences can affect or lead to errors at each of the levels below it. “Unfortunately, these organizational errors often go unnoticed by safety professionals, due in large part to the lack of a clear framework for which to investigate them” (Shappell & Wiegmann, 2000, p. 11). Described by Shappell and Weigmann (2001) as being the most elusive of latent failures, resource management, organizational climate, and organizational process are the subcategories of organization influences (Figure 5). Within the subcategories of organizational influences, resource management includes human resources related issues, monetary and budget resources issues, and issues regarding equipment and facilities. Organizational climate covers issues dealing with organizational structure, polices, and culture. The last category of organizational influences includes operations procedures and oversight (Shappell & Wiegmann, 2000, pp. 11-12).

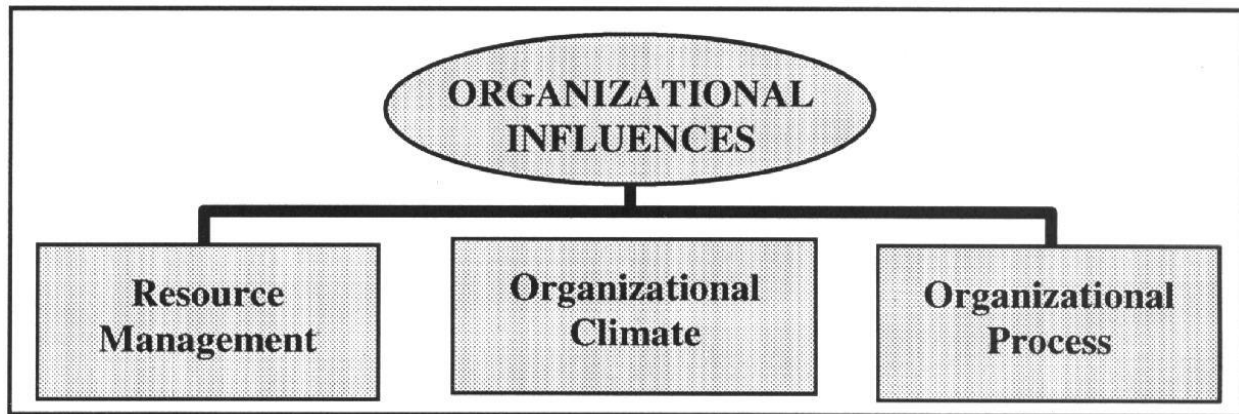


Figure 5

HFACS – Categories of unsafe supervision (Shappell & Wiegmann, 2000, p. 11).

On the surface, a standardized system for classifying errors should make accident cause assignment and analysis more accurate and tractable. Shappell and Wiegmann (2001), the creators of HFACS, use as an example an HFACS analysis of military pilot accident data to show that the system found an increase in skill-based errors and associated this with cutbacks in flying time. However, historical evaluations have found these classification systems to only be as effective as the data fed into it. In other words, “historically, accident investigators have focused on human operator error much more than on organizational factors – in part because it is difficult to be certain of the role of the latter in any given accident” (Dismukes, 2010, p. 353).

Human Factor Focus

For the purposes of this study, further review of relevant literature will be focused on four topics identified during the review of Reason’s Cumulative Effect Theory and the HFACS. Specifically, crew resource management (CRM), fatigue, spatial disorientation (SD), and situational awareness (SA) were identified as playing major roles in unsafe supervision, preconditions for unsafe acts, and unsafe acts.

Crew resource management was identified as a major part of the unsafe supervision and preconditions for unsafe acts levels. Within the structure of the unsafe supervision level, CRM plays an active role in three of the four categories including inadequate supervision, planned inappropriate operations, and supervisory violations. Under the category of substandard practices of operations within the second level of the HFACS, CRM also plays a vital role. CRM has its own subcategory including failures to back-up, communicate, coordinate, conduct adequate briefs, use all resources, and failures of leadership.

Fatigue was identified as a major factor in the second level of the HFACS as well. The substandard conditions of operators category contains three subcategories including adverse mental states, adverse physiological states, and physical and mental limitations. Each of the three subsections can be adversely affected by varying levels and influences of fatigue. Better understanding of fatigue is required to understand its relationship with many conditions that can lead to human factor errors.

As part of the unsafe acts section, spatial disorientation will be researched in detail. The review of spatial disorientation is intended to provide a better understanding of the subsection entitled perceptual errors. More specifically, defining spatial disorientation and the perceptual errors that can occur because of it will provide better understanding into how automation can aid or distract from preventing and or treating spatial disorientation.

Situational awareness was found to be present in the skill-based errors and decision errors category of unsafe acts. Skill-based errors such as prioritization errors, omitted steps or procedures or control errors can all be attributed to improper or complete loss of situational awareness. Situational awareness has an extremely large influence on decision errors as well. A loss of situational awareness or poor situational awareness can cause misdiagnosed emergencies,

individual abilities to be exceeded, poor decision-making, and a variety of other decision-based errors. The review of CRM, fatigue, spatial disorientation, and situational awareness will provide vital insight into human factor errors as well as assist in defining criteria for the analysis of human factors within the confines of this project.

Crew Resource Management

“Since the genesis and initial investigation into how crew interaction influences the flight process, the concept of CRM has been developed into an important aspect of aviation” (Salas, Maurino & Curtis, 2010, p. 5). The growth of the aviation industry has produced constant technological advancements, thus adding measures of reliability and in so doing introduced greater levels of automation. Directly proportional to the increase in automation and technological reliability in aviation is a shift in safety focus from technical to individual human factors and team performance. This shift in focus spurred the “development of what is now known to the aviation industry as crew resource management (CRM) in 1979, and the implementation of it by U.S. Airlines beginning in 1981” (Salas, Shuffler & Diaz Granados, 2010, p. 258).

“Though first introduced to pilots, CRM training has since spread to others within aviation, such as air traffic controllers and maintenance personnel, and beyond, e.g. health care professionals, first responders, off-shore oil producers” (Salas, Wilson, Burke, Wightman & Howse, 2006, p. 6). Crew resource management (CRM) is defined by Salas, Prince, Bowers, Stout, Oser & Cannon-Bowers (1999) as being a set of teamwork competencies that allow the crew to cope with situational demands that would overwhelm any individual crewmember (p. 163).

Similar to the manner in which technology has advanced to meet reliability needs, CRM has continuously evolved to meet technological and human constraints since its introduction. In addition, “advances in teamwork, team process, and team competencies have enabled a richer understanding of their significance in aviation crew performance” (Salas, Shuffler & Diaz Granados, 2010, p. 253).

This section will provide a brief history of the evolution of CRM and outline factors that influence crew performance. The six generations of evolution will be discussed in detail; before transcontinental travel was commonplace, CRM evolved at roughly the same pace, but completely independently of one another in Europe and North America. Thus, differences exist in the first four generations of evolution on each continent, but the commonalities between the development of CRM during the first four generations of evolution on the two continents will be highlighted.

History of CRM

Throughout its 30-year existence, CRM has been constantly in a state of evolution and change. CRM was originally known as cockpit resource management, but changed to crew resource management as its scope expanded beyond the cockpit. Research and training in this subject area have included, but not been limited to, team composition, cohesiveness, communication, leadership, crew behavior, evaluation methods, training development, and implementation methods. “The development of CRM has resulted in a shift from the individualistic focus of training technical skill to the complexity of teamwork that affects standard flight operations” (Salas, Maurino & Curtis, 2010, p. 6).

First generation CRM was heavily focused on classical management development and individual skills, specifically attitude, communication, and leadership. First generation CRM’s

“safety paradigm was that safety was a function of flight-crew performance exclusively” (Maurino & Murray, 2010, pp. 10-3). This model described individuals as either possessing the “right” or the “wrong stuff.” Focus of this generation was to prevent accidents caused by flawed flight-crew performance, or fixing the “wrong stuff” (Maurino & Murray, 2010, pp. 10-3-10-4).

The first generation of CRM was met with resistance, and spurred the development of the second generation. The second generation also focused on attitudes, communications, and leadership; however, it broadened its focus to include the concepts of situational awareness and stress management along with conceptual error chain and decision making models. The ideas of the “right” and “wrong stuff” were eliminated in this generation of CRM, and training was focused on improving crew performance as a result of improved crew synergy (Maurino & Murray, 2010, pp. 10-3-10-4).

The first two generations of CRM training included role-playing, non-aviation related games, and maintained a distinct separation from technology and its interaction with CRM. The integration of the “glass cockpit” drove the development of the third generation of CRM. The focus of the third generation emphasized dynamic environments and the cognitive dimensions of the small teams acting in those environments. This generation revisited the human-machine interface and introduced the concepts of mental models, stress and fatigue management, automation management, vigilance, and human reliability. The development of knowledge and understanding were vital to this generation and were a stark contrast to simply improving skills. Additional monumental changes in the third generation included the view that CRM was to be considered proactive versus reactive, the first attempts to assess CRM training, and the expansion of out-of-cockpit training to include the entire flight crew, maintenance personnel, dispatchers, and air-traffic controllers (Maurino & Murray, 2010, pp. 10-3-10-4).

The early 1990s saw the advent of the fourth generation of CRM caused by “the recognition that safety as an outcome is the consequence of the global health of the system, and that training is a tool to help the process and therefore, to influence the outcome” (Maurino & Murray, 2010, p. 10-4). The fourth generation of CRM focuses on improving a multitude of system components to improve system performance. It introduces a variety of issues like interaction between teams, shared mental models, status and role, and organizational synergy. This generation also expanded the role of maintenance personnel and air-traffic controllers, added additional aviation related personnel to participate in CRM training, and introduced a focus on cultural issues. The fourth generation of CRM also incorporates Company Resource Management and Organizational Recourse Management. Both concepts deal with the benefits of CRM reaching beyond safety to include service quality, job satisfaction, and cost efficiency (Maurino & Murray, 2010, pp. 10-3-10-4).

Maurino and Murray (2010) point out since the time of broad Trans-Atlantic consensus within a context of increasing awareness of cultural issues, there has been a further and most significant milestone (10-5). They further explain this CRM milestone as a transition from broad strategic encompassing goals of “safer flight,” to a more focused or tactical emphasis on what CRM was attempting to achieve during each flight. Aiding this transition in the late 1990s was the introduction of line operation safety audits (LOSA). LOSAs were a method by which trained observers would monitor flight crews during normal operations. The goal was for the observers to monitor what the crews did to fly safely from takeoff to landing. The findings of LOSAs, past CRM data, and similarities with classic CRM “skills” yielded substantial findings. It became obvious that human error was inevitable and furthermore that pilots were using effective strategies and countermeasures to combat human error. These strategies occurred at three levels–

avoiding or minimizing error, stopping error early before it became consequential, and mitigating effects of errors that had not been stopped. From these strategies emerged error management, and its development and incorporation into CRM as the fifth generation (Maurino & Murray, 2010, pp. 10-5).

CRM evolved yet again with the progression of error management into threat and error management (TEM). As LOSA research continued, the operational environment was identified as playing a large role in error management. The operational environment was conceptually described as a threat, or potentially negative events or situations out of the control of the flight crew requiring their immediate actions to manage. The sixth and most recent generation of the CRM evolution uses TEM as its foundation, and coupled with the desire to increase cultural awareness, has become the focus of modern-day CRM implementation and training (Maurino & Murray, 2010, pp. 10-5).

Crew Performance Factors

“Aviation crews are like any other type of team. For them to be effective the members need to perceive that they are a team, understand each other’s roles, and be well trained on teamwork competencies” (Salas, Shuffler & Diaz Granados, 2010, p. 263). Salas, Stagl, Burke, & Goodwin (2007) define a team as a complex entity consisting of: (1) two or more individuals (2) who interact socially and (3) adaptively, (4) have shared or common goals, and (5) hold meaningful task interdependencies; it (6) is hierarchically structured and (7) has a limited life span; in it (8) expertise and roles are distributed; and it is (9) embedded within an organizational/environmental context that influences and is influenced by ongoing processes and performance outcomes (p. 189). This section will define teamwork, discuss factors affecting teamwork and crew performance, and briefly explain team errors.

Teamwork Defined. “Teamwork is defined as a set of behaviors, cognitions, and attitudes that are enacted in order to achieve mutual goals and meet the demands of the outside environment” (Salas, Shuffler & Diaz Granados, 2010, p. 253). A team able to work cohesively together can efficiently accomplish mutual goals as referenced in the definition of a team and teamwork. However, accomplishing mutual goals is dependent upon a multitude of factors. Leadership, shared mental models, adaptability, and communication will be discussed as examples of factors that impact crew performance. No inference will be made that this group of factors form an autonomous list, but rather they are a sample of factors that affect crew performance.

Factors Impacting Teamwork and Crew Performance. “Team leaders in complex systems contribute to the climate in which the group operates, whether autocratic, democratic or something in between” (Strauch, 2004, p. 100). The captain of any flight assumes responsibility for the aircraft and entire crew; however, that responsibility in itself does not guarantee quality leadership. The quality of any aviation crew’s performance directly relates to the leadership skills of the captain. Later generations of CRM also broaden the scope of leadership within a flight crew, citing the leadership responsibilities many subordinate crewmembers have that contribute to the safe operation of any flight. Quality leaders attend to both operating tasks and subordinate concerns. In addition, quality leaders should not be overbearing and should foster open communication. Negative results can arise from overbearing leadership, especially in high stress situations such as emergencies.

A leader must also recognize and understand team dynamics and how cultural differences can affect performance and interaction. Another vital aspect of leadership is the ability to understand how “individual characteristics might interact with automation to affect team

performance” (Bowers, Oser, Salas& Cannon-Bowers, 1996, p. 247). A leader’s clear conveyance of expectations, understanding of flight progress, and continual evaluation of the flight and crew performance is also essential to prevent an ambiguity and a breakdown in crew coordination (Strauch, 2004, pp. 264-265).

Team functionality also depends on shared mental models. Rouse and Morris (1985) define mental models as the mechanisms whereby humans can generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of future system states (p. 7). Multiple shared mental models can exist for tasks, technology, teamwork or other relevant items to aviation operations. Task mental models would include knowledge and experience regarding task completion and procedures. Technology mental models can cover technological systems and other relevant equipment and a crew or individual’s understanding of its function and operation. Shared mental models will facilitate team members to use technology or equipment to “1) interact with other team members, 2) access the information presented to other team members, and 3) control the system from other team members” (Strauch, 2004, p. 96). This ability coincides with teamwork mental models in many ways, but teamwork mental models also include interdependencies of individual roles and knowledge of others’ roles. Shared mental models also improve team function by allowing the team to anticipate actions and strategy formation (Strauch, 2004, p. 266).

A team’s ability to adapt to situations as they arise is essential for performance at high levels. Unexpected technical, mechanical, external or human-based issues can easily negatively influence safety and degrade crew coordination. Adaptability will vary depending on knowledge, experience, and cognitive ability. It also can be greatly influenced by crew mix and leadership presence. The need to be adaptable deals with unexpected situations; it is thus very difficult to

train for. Extensive experience and a great deal of training scenarios are required to provide a solid base to make decision and instill adaptive qualities (Strauch, 2004, p. 270).

Communication has been mentioned or alluded to in all of the previously discussed crew performance factors. This is important to note because “a team needs to communicate with one another in order to develop a shared mental model, team situational awareness, and adaptability” (Strauch, 2004, p. 271). A breakdown or problem with communication is often implicated in aviation accidents and incidents. This further supports the importance of effective and explicit communication skills in the aviation industry. The type of communication is also important to consider when dealing with the efficiency of team performance. Proactive communication, concise communication, and closed-loop communication have proved effective in teams functioning at high levels. The meaning of proactive and concise communication are clear – closed-loop communication involves the receiver of a message acknowledging receipt of the message as well as the sender verifying it for accuracy. Communications is not limited to the cockpit, but rather extends to all interaction a flight crew may have at any time during the flight. As previously mentioned when discussing leadership, the captain should encourage open lines of communication to help overcome obstacles to communication and obstructive reaction in times of high workload or stress (Strauch, 2004, pp. 271-272).

Team Errors. In order for team errors to be committed, there must be two or more individuals involved with the operation of a system or execution of a task. Team errors include but are not limited to, failing to notice or respond to another’s errors, excessively relying on others, inappropriately influencing the action or decisions of others, and failing to delegate team duties and responsibilities (Strauch, 2004, p. 93).

Failing to notice or respond to another's errors is the most common multi-operator team error. This error can occur in two different ways. The first is when an operator fails to attend to or monitor the actions of another. The second way this error can occur is when individuals notice errors of another, but fail to respond or correct the error for any reason (Strauch, 2004, p. 93).

Excessively relying on others is another common team error. This error occurs extensively when system operators have a variety of experience and expertise involving a specific task or system. This error can occur when an individual fails to perform their own duties because they rely so heavily on someone else, when a person who is relied upon makes a mistake, or when the person being relied upon does not possess the necessary skills for the task or operation to be performed. This error is prevalent when junior team members disregard their own knowledge when confronted with team members who possess much more experience, seniority, authority, or status (Strauch, 2004, p. 94).

Operators who inappropriately influence the actions or decisions of others is another type of team error. This error is often seen in dynamic stressful situations when certain operators have extremely strong or weak personalities. An individual can inappropriately diagnose a situation and exert an error influence on their team member who may have assessed the situation correctly. Consequently, multi-operator error may occur because of one team member's interference with other team members' assessments of the situation (Strauch, 2004, p. 94).

Failing to delegate team duties and responsibilities can also lead to catastrophic multi-operator errors. This type of error often occurs when an abnormality has occurred and demands the attention of the crew. If there is not a clear and concise delegation of duties among the crew, effective control of the system or effective response to the abnormality can easily suffer. This

type of multi-operator error was present in many of the cases that spurred the development of cockpit resource management (Strauch, 2004, pp. 94-95).

Fatigue

“Fatigue is classically defined as a decrease in performance or performance capability as a function of time on task” (Mallis, Banks & Dinges, 2010, p. 401). It is one of the most prevalent and historically recognized aviation human factors. The U.S. Department of the Army (2000) further defines this classical definition of fatigue as “the state of feeling tired, weary or sleepy that results from prolonged mental or physical work, extended periods of anxiety, exposure to harsh environments, or loss of sleep” (U.S. Department of the Army, 2000, pp. 3-13). The effects of fatigue have been extensively researched and documented throughout the history of aviation and were the primary cause of “the now 70-year-old federal duty time regulations in U.S. commercial aviation” (Mallis, Banks & Dinges, 2010, p. 401).

To understand why fatigue affects the body, the circadian rhythm of the human body must be examined. Almost all biological organisms will show physiological and behavioral changes based on the 24-hour rotation of the Earth. The body undergoes highs and lows in its circadian rhythm, depending on the time of day, which can cause changes in “many physiological and behavioral functions, including sleep cycle, digestion, hormonal activity, and body temperature” (Strauch, 2004, p. 55), as well as plasma cortisol, plasma melatonin, alertness, subjective fatigue, and cognitive performance. The human body simply cannot operate twenty-four hours a day seven days a week. Everyone requires sleep, and in consistent intervals and amounts (Mallis, Banks & Dinges, 2010, pp. 401-404).

Interacting with the human circadian cycle is the homeostatic sleep drive. “Consequently, three factors can result in elevated homeostatic sleep drive: (1) increasing time continuously

awake; (2) inadequate sleep duration for one or more consecutive days; and (3) sleep that is physiologically disrupted (fragmented) due to medical conditions or environmental factors” (Mallis, Banks& Dinges, 2010, pp. 403-404). A human’s circadian rhythm and homeostatic sleep drive oppose each other and promote a balance that turns into the fundamental need for the human body to sleep during its biological night (Mallis, Banks& Dinges, 2010, pp. 401-404).

The normal workday of a human is based on the 24-hour rotation of the earth. The body has the tendency to require sleep based on the light and dark progression of the day. In a 24 hour period, the average human requires approximately seven to eight hours of sleep, leaving approximately 16 waking hours. The feeling of needing an afternoon nap, or feeling lethargic or weary in the afternoon is simply a low point in the biological cycle. By nighttime, or on average nine o’clock, that homeostatic sleep drive is at its peak and the body has the overwhelming urge to sleep for the night (Mallis, Banks& Dinges, 2010, pp. 403-406).

Circadian rhythms modulate human alertness and performance and simply were not designed to function under the pressure of a 24-hour schedule. It is further understood “fatigue cannot be eliminated from aviation operations because of the inherent schedule requirements for trans-meridian travel, irregular and unpredictable schedules, long duty days, early report times, night flights, and reduced sleep opportunities” (Mallis, Banks& Dinges, 2010, p. 402). With the realization fatigue cannot be avoided, understanding the effects of fatigue are important for anyone in the aviation industry. The effects include, but are not limited to degraded human performance, diminished alertness, impairment of information processing, diminished memory, impaired communication skills, and slowed reaction time. This section will further define fatigue by explaining the three types of fatigue, and will discuss the effects of fatigue on performance and techniques to prevent fatigue.

Types of Fatigue

The three types of fatigue are acute, chronic, and cumulative. Fatigue is cumulative in nature and can result from a multitude of causes. Some fatigue yields little or no disruption in performance whereas other levels can render an individual incapable of completing simple tasks. Some major issues leading to fatigue are the time of day, disrupted circadian rhythms, substantial sleep loss over a 24-hour period, and accumulated sleep loss over several days.

Acute Fatigue. Miller (2001) defines acute fatigue as fatigue that develops within one work period and from which recovery occurs during one major sleep period (p. 5). A second definition states, “acute fatigue is associated with physical or mental activity between two regular sleep periods” (Department of the Army, 2000, pp. 3-13). Regardless of the definition, it is obvious that acute fatigue is the lowest level of fatigue and is manifested after relatively short periods. This paper will use the first definition of acute fatigue and relate it to the human intrinsic biological clock within a 24-hour cycle.

It is important to note that when dealing with acute fatigue, mental deficits like inattention, distractibility, errors in timing, neglect of secondary tasks, loss of accuracy and control, lack of awareness of error accumulation, and irritability will be noticed before any physical signs of fatigue will be felt (Department of the Army, 2000, pp. 3-14).

Chronic Fatigue. Chronic fatigue is much more dangerous occurring “over a longer period and is typically the result of inadequate recovery from successive periods of acute fatigue” (Department of the Army, 2000, pp. 3-14). This type of fatigue cannot be recovered from quickly; it may take several weeks to adequately recover from chronic fatigue. During chronic fatigue not only does an individual experience being physically tired but also the feeling of being mentally tired is experienced (Department of the Army, 2000, pp. 3-14).

Chronic fatigue can manifest itself in all the ways acute fatigue does. In addition, chronic fatigue can cause an individual to experience insomnia, feel depressed, lose weight, exercise poor judgment, lose their appetite, experience slowed reaction time, as well as experience poor motivation and performance on-the-job (Department of the Army, 2000, pp. 3-14).

Cumulative Fatigue. Cumulative fatigue can also be compared to motivational exhaustion or burnout. It occurs when chronic fatigue persists and is never dealt with or recovered from. Cumulative fatigue usually will occur over a great deal of time but can occur more quickly depending on the nature of disruption to circadian rhythms, work performed, and rest that occur. This type of fatigue will eventually lead to the body no longer being able to perform or shutting down.

Effects of Fatigue on Performance

Understanding the three types of fatigue and symptoms associated with each is extremely important. To better understand the effects of fatigue, this section will discuss how those symptoms manifest, influence performance and how they can be detrimental when combined with automated systems. Reaction-time changes, reduced attention, diminished memory, changes in mood and social interaction, and impaired communication will be discussed along with work factors conducive to fatigue affecting performance.

Reaction-time changes can be seen in two distinct ways, depending on the level of fatigue combined with the individual involved. A decrease in reaction time can occur because an individual may react impulsively. A decrease in reaction time due to fatigue usually results in a rash, uninformed, or poor decision. A decrease in reaction time is usually a result of the common behavior that accompanies the onset of fatigue, such as decrease in motivation or sluggishness (Department of the Army, 2000, pp. 3-14).

Combined with automation operation or monitoring reaction-time change can adversely affect safety. Reacting impulsively can lead to decisions based on a small amount of information or the wrong information about a system, the crew, the environment or the aircraft. Rash reactions also run the risk of erroneous inputs or commands. An increase in reaction times can also affect safety but in different ways. Lethargic or slowed reaction can allow errors to occur or parameters to be exceeded without timely intervention.

Reduced attention is another common effect of fatigue. Reduced attention can result in the tendency to overlook or misplace sequential task elements. An example of this would be omitting a step on a checklist or not using a checklist at all. Automated systems require a number of tasks to be performed sequentially, and omitting or conducting steps out of order to lead to undesirable consequences. Reduced attention also includes preoccupation with a single task or its elements. This type of failure can be catastrophic if one or both pilots become fixated on a light or indication in an automated system and lose situational awareness of the aircraft altitude or obstacles in its flight path. Reduction of audiovisual scan both inside and outside the cockpit and a lack of awareness of poor performance are also results of reduced attention. Errors of scan omission or missed indications in automated systems followed by the inability to recognize a decrease in performance are examples of how reduced attention can once again adversely affect flight safety (Department of the Army, 2000, pp. 3-15).

Diminished memory is another negative effect of fatigue on human performance. A decrease in short term memory and processing capacity, difficulty adapting to change, inaccurate recall of operational events, neglect of peripheral tasks, and a decreased ability to integrate new information and solve problems are all results of diminished memory's effect on performance. Analyzing all the effects of diminished memory, an operator's inability or difficulty analyzing

and solving problems presents the gravest danger when dealing with automated systems.

Neglecting tasks such as configuring automated systems properly for takeoff or landing could also introduce a potentially fatal problem (Department of the Army, 2000, pp. 3-15).

Changes in mood and social interaction can also result from fatigue and greatly affect human performance. A common characteristic of fatigue is irritability; this symptom can manifest with individuals being combative. Forms of depression are also related to fatigue and can lead to individuals withdrawing socially. A major concern with operators of automated systems deals with their knowledge of the system and familiarity with the way it operates. Confusion, unexpected operation or false alarms in automated systems can easily lead to irritability. Depression and social withdrawal will greatly influence an individual's crew coordination and motivation, yet again posing problems when dealing with automated systems (Department of the Army, 2000, pp. 3-15).

The last major effect of fatigue on performance that will be discussed in this section is impaired communication. The importance of communication was outlined in the previous section dealing with crew resource management, and the negative effects related to communication are just as important to understand. An operator's ability to communicate and receive information is affected due to misinterpretation, omission of important details, or disregarding portions of information they receive. All vital components of good crew resource management, and without which automated system interaction can be impaired. Changes in pronunciation, rate of speech, tone, and volume also can be adversely effected due to fatigue (Department of the Army, 2000, pp. 3-15).

Prevention of Fatigue

Research outlining fatigue, risks associated with restriction of sleep, loss of sleep, circadian desynchronization and the relationship between sleep and circadian systems began around 1930. Around this same time, duty and flight time regulations were originally developed. Original research was based on time-on-task theories rather than sleep loss and circadian misalignment. “Although a large body of scientific research in the past 40 years has established that the interaction of sleep and circadian dynamics determines fatigue levels in otherwise healthy individuals such as pilots, the prescriptive scheduling regulations from the 1930s remain in place today with very few changes” (Mallis, Banks & Dinges, 2010, p. 419).

Current commercial aviation operations place pilots at risk for fatigue related to operational challenges including irregular and unpredictable schedules, long duty days, early report times, night flights, reduced sleep opportunities, and circadian disruption. These risks are “further complicated by highly automated cockpits that require minimal interaction with aviation systems, which results in a high requirement for relatively passive vigilance in flight crews” (Mallis, Banks, 2010, p. 414). Prolonged vigilance and sustained attention are difficult tasks to perform reliably when fatigued, but vital to the safe operation of automated aviation systems (Mallis, Banks & Dinges, 2010, p. 414).

There is a clear need to “develop scientifically valid fatigue-management approaches to mitigate sleep loss, enhance alertness during extended duty periods and cope with circadian factors that are primary contributors to fatigue-related aviation incidents and accidents” (Mallis, Banks & Dinges, 2010, p. 402). The fatigue risk management system (FRMS) is an evidence-based and non-prescriptive approach for addressing performance, safety levels, and fatigue challenges associated with aviation operations. Combined with existing safety management

systems, this approach can be implemented for the measurement, management, and mitigation of the risks associated with fatigue. In addition to this system, research in bio-mathematical scheduling tools is being conducted and implemented regarding mitigation of the risks associated with fatigue. The goals of this effort are to predict times neurobehavioral functions and performance will be maintained, establish time periods for maximal recovery sleep, and to determine the cumulative effects various work-to-rest schedules have on overall performance (Mallis, Banks & Dinges, 2010, p. 420).

“Humans are often unable to accurately estimate how variable or uneven their alertness and performance have become due to inadequate sleep or working at night” (Mallis, Banks & Dinges, 2010, p. 427). Because fatigue cannot be prevented, this fact provides evidence as to the importance of continuous fatigue prevention for aviation personnel, and especially for aviation personnel requiring elevated vigilance due to automated systems.

Controlling the sleep environment by maintaining a dark and quiet setting, and avoiding work or other cognitive activities in bed tend to improve quality of rest. Adhering to a set work schedule or adjusting to shift work is vital to getting adequate rest. To help prevent circadian desynchronization, it is recommended to maintain a constant sleep schedule even on days off, do not go to sleep on an empty or full stomach, and avoid caffeine consumption within six hours of attempting to sleep. It is further recommended that one maintain a healthy lifestyle to include proper diet and exercise as well as taking naps when needed (Department of the Army, 2000, pp. 3-17-3-18).

“Operational demands resulting in extended work days, increased workload levels, reduced sleep opportunities and circadian disruption continue to pose significant challenges during aviation operations” (Mallis, Banks & Dinges, 2010, p. 430). Fatigue cannot be prevented

and is closely intertwined with physiological and behavioral functions. Acute, chronic, and cumulative fatigue are all aggregate in nature, and all lead to degraded performance on a variety of levels. The requirements of prolonged vigilance and sustained attention dealing with automation are extremely difficult tasks to perform reliably when dealing with fatigue. Many preventive measures are available to manage fatigue, but programs to deal with fatigue in commercial aviation operations are extremely outdated and do not correspond to current research.

Spatial Disorientation

Spatial disorientation is one of the most common and most deadly challenges facing aviators. Spatial disorientation “refers to a false perception of distance, attitude, or motion relative to the plane of the Earth’s surface when a correct perception is necessary for controlling position, attitude or motion” (Collins, 1995, p. 1). It can occur during every phase of a flight from ground taxi to landing. No set conditions exist that dictate when it will occur, therefore a pilot’s knowledge of spatial disorientation, the illusions that cause it, the human systems behind the illusions, and a knowledge of system operation and displays are vital to combating spatial disorientation. The human visual, vestibular, and proprioceptive systems provide spatial orientation but are not without error. The systems have a number of illusions that may be caused by a variety of factors such as acceleration, angular movements or perception. The human body’s interpretation of these factors or conflicting interpretations lead to spatial disorientation.

Visual System. Spatial disorientation is the mistaken perception of one’s position; in contrast, spatial orientation is defined as, “our natural ability to maintain our body orientation and/or posture in relation to the surrounding environment at rest and during motion” (Antuñano, 2011, p. 1). Humans’ eyes, or the visual system, provide 90% of the information the human body

uses to orientate itself with respect to the Earth. The visual system is by far the most reliable of any human sensory system. Visions oftentimes will override mismatched signals from other sensory systems, with the brain unaware conflicting signals were received. Vision is very reliable; however, vision is susceptible to illusions or mistakes in interpretation, which can lead to spatial disorientation (Wynbrandt, 2004, pp. 1-2).

The aerial perspective illusion is very common and will oftentimes go unrecognized. Aerial perspective deals with the way that a pilot interprets what they are seeing from the air. Perception is usually tied to experience or in reference to known data but can be misinterpreted very easily. For example, an aircraft on final approach may view a runway in a multitude of ways depending on the width, length, lighting, the sloping of the runway itself or the sloping terrain surrounding an airfield. An example of this would be an approach over flat terrain with a down sloping runway. The perception can give the pilot the illusion they are on a low altitude final approach; if the pilot responds to this illusion they will slow the aircraft that may result in a stall. Just the opposite is true for an approach over flat terrain with an up sloping runway. The pilot may perceive the aircraft is on a high-altitude final approach and may lower the nose. If there is insufficient altitude the pilot may end up running the aircraft into the ground (Antuñano, 2011, pp. 2-3).

Another example of a visual illusion is the black hole approach illusion. Black hole illusion occurs during final approach in night operations with no moon or stars present, over water, or over terrain with no lights to a lighted runway. A pilot will believe that the runway is tilted left and up sloping. If a visible horizon is present this illusion can be easily overcome; however, like the aerial perspective illusion, many variations to the illusion exist. A very dangerous version of this illusion occurs when on final approach to a runway with no lights

before it and rising lighted terrain directly after. The pilot will perceive a high altitude approach, and the reaction could nose the aircraft over and contact the ground well short of the runway (Antuñano, 2011, p. 3).

Staring at a fixed point of light during hours of darkness causes the auto kinetic illusion. The light source could be a star, any light on the ground or any visible light on the horizon. After staring at the light, the pilot may get the sensation that the light is moving. If fixated on the light, the pilot may also get the impression that the light is moving in their path of flight or directly toward the aircraft. If the pilot remains fixated on the light they may not pick up any other visual cues that would tell them their perception was not accurate (Antuñano, 2011, p. 4).

False visual reference illusion can be extremely dangerous for any pilot that may experience it. This illusion occurs when a pilot references something other than the viewable horizon as their horizon. They may use a cloud layer, a ridgeline or a string of lights on the horizon. The pilot will use the false horizon and orient the aircraft in reference to it. If unrecognized, the aircraft may be placed in a turn, climb, descent or any combination of the above (Antuñano, 2011, p. 4).

Thevection illusion is another visual illusion that can cause any pilot to become disorientated.vection illusions deal with the pilot's false interpretation of another aircraft or object's movement as their own. This illusion is very common and can be quite confusing if proper scanning and use of other types of vision are not incorporated (Antuñano, 2011, p. 4).

Many other visual illusions and variations of those mentioned above have the possibility of occurring during flight. Proper use of visual references and experience will contribute greatly to safe operation of any aircraft. Many techniques are used to identify and work through visual illusions, comparing the known size of an object, comparing the known shape of an object, using

known distance of illumination, an object's position or layer in the field of view, and using texture and contrast of known objects. It is crucial for the pilot to know what he/she is looking for and be able to identify illusions in an attempt to avoid spatial disorientation (Antuñano, 2011, p. 4).

Vestibular System. The vestibular system is the human body's secondary positioning system. The primary purpose of the system is to maintain balance, which is achieved by signals being sent from the inner ear to the brain. Each ear consists of two structures to achieve this communication, the semicircular canals and the otolith organs. Both provide the brain with gravity and motion information, which can supplement vision by providing reference to position or motion. These organs' signals can be misleading due to many factors, such as illness, dizziness or one of many illusions associated with the vestibular system (Wynbrandt, 2004, p. 2).

The semicircular canals are associated with angular or somatogyral illusions. The semicircular canals consist of three tubes, which are perpendicular to each other. Each tube contains sensory hairs and fluid, which moves with the motion of the head or the body. Fluid movement within the canals provides the brain with signals, which produce the human body's perception of pitch, roll, and yaw. The four somatogyral illusions associated with the semicircular canals are the leans, graveyard spiral, graveyard spin, and the coriolis illusion. Each illusion varies in severity and is more prevalent during conditions of unreliable visual reference and angular motion (Wynbrandt, 2004, p. 2).

The most common of the four illusions is the leans. The leans occur after a pilot levels the wings following a prolonged unrecognized turn. This illusion is due to the semicircular canals not being able to detect rotational acceleration that results in turns that are less than two degrees per second. If the semicircular canals were stimulated during the turn the pilot would

feel as if they were straight and level, when actually in the turn. When the pilot actually leveled the wings, they would have the sensation of entering a turn in the opposite direction. A common response is for the pilot to lean in the direction of the original turn, in an attempt to regain what they perceive as a correct orientation to the horizon (Department of the Army, 2000, pp. 9-14-9-15).

Another illusion dealing with unrecognized turns is the graveyard spiral. This illusion occurs during high-speed descents. During the descent the wings can drop causing the aircraft to enter a turn. If the turn is less than two degrees per second the pilot may not realize they are in a turn. As the speed during the descent increases, the turn may also increase in severity. As the aircraft spirals toward the Earth, the pilot will sense the rate of descent, but will not realize they are in a turn. Because the turn gradually was built up and is now coupled with the aggressive rate of descent, control movements will only aggravate the turn (Department of the Army, 2000, pp. 9-15-9-16).

The graveyard spin is not as common as the leans, but the graveyard spin is much more dangerous. Graveyard spins occur after a prolonged turn, greater than 20 seconds, when the semicircular canals are stimulated and the pilot perceives that they are no longer in a turn, or that the severity of the turn is decreased. When the pilot levels the wings, they will perceive that they have entered a turn in the opposite direction. Flying straight and level creates a sensory conflict that could result in the pilot reentering their original turn. During the duration the pilot may be losing altitude due to the prolonged turn, which if not arrested could result in fatality (Department of the Army, 2000, pp. 9-15-9-16).

The most dangerous of the three somatogyral illusions is the coriolis illusion. Coriolis illusion involves the simultaneous stimulation of two semicircular canals, caused by sudden or

abrupt tilting or movement of the head while in a turn resulting in the oftentimes overwhelming sensation of movement on all three axis at once. The Coriolis illusion can immediately disorientate a pilot and cause them to lose control of the aircraft (Antuñano, 2011, p. 4).

The second of the two vestibular sensory organs are the otolith organs. “The otolith organs are small sacs at the base of the semicircular canals. They are embedded with sensory hairs and contain a gelatinous membrane with chalk-like crystals – called otoliths” (Wynbrandt, 2004, p. 2). The otolith organs provide the body with the sense of acceleration and deceleration. The membrane moves when the head or body are in motion and pushes against the sensory hairs that results in a feeling of gravity and accelerative forces. Three illusions are associated with the otolith organs, which are referred to as somatogravic illusions (Wynbrandt, 2004, p. 2).

The first of the three somatogravic illusions is the oculo-gravic illusion. “The oculo-gravic occurs when an aircraft accelerates and decelerates” (Department of the Army, 2000, pp. 9-17). When a pilot increases their speed, the gelatinous layer containing the otolith organ is shifted aft. If the pilot then fails to crosscheck the instruments, they will perceive the aircraft to be in a nose high attitude. The natural reaction if the pilot perceives attitude would be to induce a dive. The inverse illusion and reaction is true with a deceleration (Department of the Army, 2000, pp. 9-17).

The second somatogravic illusion is the elevator illusion. This illusion occurs during upward acceleration and is commonly experienced by pilots encountering updrafts. The inputs supplied by the pilot’s otolith organs cause the sensation of a nose high attitude and the natural response is to initiate a dive. The opposite is true regarding the last of the three somatogravic illusions. The oculo-gravic illusion results in the sensation of a nose low attitude and the pilot has a tendency to pull back on the stick or reduce speed. This a common occurrence when

encountering downdrafts or when a helicopter enters autorotation (Department of the Army, 2000, pp. 9-18)

Proprioceptive System. The proprioceptive system consists of the “nerves in the skin, muscles, joints, and internal organs, along with hearing” (Wynbrandt, 2004, p. 2). The phrase “seat of the pants flying,” is associated with the proprioceptive system and the body’s interpretation of where it is in space or how it is moving through space due to forces exerted on the aforementioned body parts. The forces on the system are not as apparent as on the ground; in flight they are felt as changes in G-forces and pressures are exerted on the body. Hearing contributes to position estimation relative to a sound source or movement. Despite the fact that no illusions are directly related to the proprioceptive system, every system’s inputs are compared and the discrepancies between them are what causes disorientation (Wynbrandt, 2004, pp. 2-3).

Prevention. As with many things, experience is truly a lifesaver. Every system discussed provides signals to the brain relaying vital information to establish the human position and motion relative to the surface of the Earth. When illusions occur, the signals are contradicting each other, which if not corrected can lead to spatial disorientation. Knowing what to look for or recognizing the illusions and their symptoms is very beneficial for prevention, treatment, and avoidance of spatial disorientation.

The prevention and treatment of spatial disorientation have common practices associated with each. Trusting instruments, understanding and utilizing an appropriate digital display setup, knowledge and understanding of automated systems, and proper use of automated systems are all vital in preventing and treating the onset of spatial disorientation.

Trusting the instruments, along with understanding and utilizing appropriate digital display setups, is the most prevalent way to prevent or treat spatial disorientation. With the onset

of automation and more advanced cockpits becoming commonplace in the aviation industry these practices now coincide due the fact instruments are more often than not displayed on digital displays. Possessing relevant and appropriate information displayed will help provide adequate reference to combat the onset of spatial disorientation or treat it if symptoms are experienced. Referencing, trusting, and having confidence in instrument displays will help combat the onset of illusions; however, knowledge of location and functionality of displays is vital for the efficient use of the aforementioned displays. Experience will also improve a pilot's ability to discern what is important regarding displayed indications and the speed at which they can refer to such indications.

Along with more advanced cockpit displays, present day aircraft often have multiple automation features that can help with dealing with spatial disorientation. A detailed knowledge of automated system function along with the proper use of automated systems can greatly reduce the chances of accidents resulting from spatial disorientation. When experiencing the onset of spatial disorientation, rather than fight through the illusion on the controls, a pilot can allow the aircraft to fly itself utilizing an autopilot feature and provide the pilot time to re-orientate themselves. This is, of course, dependent on location and proximity to hazards. Many other automated features, such as ground proximity warning systems, provide extra inputs or warnings if a spatial disorientation situation has occurred.

Pilots of modern day aircraft have many automated systems to help them combat spatial disorientation. However, if they do not know how to use the systems at their disposal, or if they do not understand their operations, they may not provide help or may even be counterproductive in dangerous situations. A pilot's indecision to rely on their displays and automation usually result in accidents when spatial disorientation is present. Trusting instrument displays,

maintaining proficiency and knowledge of how automated systems are designed to operate and assist, and being familiar with spatial disorientation and its illusions are vital to combating spatial disorientation.

Situational Awareness

“Situational awareness (SA) can be conceived of as the pilot’s internal model of the world around him at any point in time” (Endsley, 1988, p. 97). Situational awareness is vital to the safe and efficient operation of any automated system and is recognized as a crucial component for success in the aviation community. Often overlooked during routine operation, a lack of situational awareness by pilots can lead to catastrophic or fatal system failures. The following discussion on situational awareness in relation to aviation automation systems will provide a brief introduction and definition of situational awareness, discuss the levels of situational awareness, and examine the negative impacts automation can have on situational awareness in complex automated aviation systems.

The automation of tasks has not removed the pilot from playing a critical part in system operation, but their role has changed from operator to system monitor. This role may not be ideally suited for humans, but automation system functionality and efficiency exceeds the possibilities of human performance. High levels of efficiency and functionality are designed to reduce operator workload and increase situational awareness. However, an increase in situational awareness by system operators has not always been achieved, and an operator’s level of situational awareness can vary as easily as the level of complexity in automation systems. System designers have strived to increase situational awareness, but in so doing have discovered many challenges (Endsley, 1996, pp. 163-164).

“Originally a term used solely in the aircraft community, situational awareness has developed as a major concern in many other domains where people operate complex, dynamic systems, including the nuclear power industry, automobiles, air traffic control, medical systems, teleoperations, maintenance, and advanced manufacturing systems” (Endsley, 1996, p. 165). Situational awareness is formally defined by Endsley (1988) as the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future (p. 97). In aviation, a pilot uses their senses and aircraft displays to form a basis for their situational awareness. Their ability to further improve their level of situational awareness is dependent upon their preconceptions, experience, training, capabilities, mission, and current workload. A pilot’s level of situational awareness forms a vital input to the pilot’s decision making process (Endsley, 1988, p. 97).

An operator’s level of situational awareness can be categorized into three distinct levels. The first, or level 1 SA, involves the operator recognizing critical environmental factors. Level 2 SA involves “understanding what those factors mean, particularly when integrated together in relation to the operator’s goals” (Endsley, 2001, p. 4). Level 3 SA occurs when an operator is able to understand future system actions or reactions based on environmental factors and system indications. The higher the level of situational awareness an operator possesses the timelier and more effective they can function (Endsley, 2001, p. 4).

“The first step of achieving SA is to perceive the status, attributes, and dynamics of relevant elements in the environment” (Endsley, 2001, p. 4). When flying, a pilot needs to perceive important situational elements such as altitude, airspeed, and location relative to their desired flight path. In addition, they must be aware of their flight system operations in reference to flight parameters and other system characteristics. They must monitor the weather as well as

other traffic and navigational data relevant to their flight. Depending on the type of aircraft and its designated tasking, additional information would need to be considered to achieve the first level of situational awareness. Any combination of the aforementioned items could severely tax a pilot, and combining them all could at times be overwhelming (Endsley, 2001, p. 4).

A level 1 SA failure would result in a pilot failing to correctly perceive crucial environmental elements. This can occur for a number of reasons, which include the data not being available, the data being hard to discriminate or detect, a failure to monitor or observe data, the misperception of data or from memory loss. Of the level 1 SA failures, to monitor or observe due to omission, distractions imposed by other relevant tasks, and a high task load are the most prevalent. Data not being available to an operator is also a large cause of failures, and is often attributed to a failure of system design or a failure of an operator to perform a necessary task. Some causes of information being difficult to detect or perceive would include inadequate lighting, high noise levels, or obstructions blocking and operators view. A loss of memory, often associated with a distraction or task saturation, negatively affects situational awareness because pilots' situational awareness is based upon their ability to rely on a number of factors in memory (Endsley, 1999, pp. 3-4).

Comprehension of the current situation, or Level 2 SA, sees a transition from the operator merely recognizing environmental factors to gaining an understanding of how factors interact and are important. When level 2 SA is reached, "the operators put together Level 1 data to form a holistic picture of the environment, including a comprehension of the significance of objects and events" (Endsley, 2001, pp. 4-5). For example, if a warning light illuminates during takeoff, the pilot must immediately determine if the warning light warrants aborting the takeoff and combine this decision with their knowledge of the remaining runway and determine if the

takeoff can be aborted safely. Pilots with less experience will be able to evaluate the elements of the sample situation, but may fall short when attempting to comprehend the severity of the entire situation and integrate the various data elements in order to make a good decision based on situational awareness (Endsley, 2001, pp. 4-5).

A lack of poor mental models, the use of incorrect mental models or the over-reliance on default values can all lead to a failure to comprehend the situation. Of the three, the lack of a good mental model is the most common; simply put, a pilot does not have a good mental model for combining information or associating that information with goals within an automated system. When a pilot has a mental model, but it is for a similar system, they can misinterpret information or misunderstand the system that leads to incorrect system diagnoses and situational awareness errors. In the absence of real-time data, pilots can rely on habitual expectations rather than current data that can lead to over-reliance situational awareness errors. Level two situational awareness errors also can be caused by memory limitations or when significant information is simply not comprehended or properly integrated (Endsley, 1999, pp. 3-5).

Lever 3 SA or projection of future status is the highest level of situational awareness. This level of situational awareness based on being able to predict the future state of the system by evaluating the current state and knowledge of the system dynamics is “critical for allowing decision makers to function in a timely and effective manner” (Endsley, 1996, p. 166). Only with comprehensive and accurate situational awareness can operators accurately diagnose and correct automated system deviations and provide the proper inputs for automated system operation (Endsley, 2001, p. 5).

Over-projecting current trends, a lack of a mental model or a poor mental model can lead to a level 3 situational awareness failure. Projecting future actions to the state of the system is an

extremely demanding task. This failure can occur frequently when pilots have a high level of situational awareness but are not capable of projecting future actions (Endsley, 1999, pp. 3-5).

Automation was designed to improve situational awareness by reducing stress, workload, and the overall complexity of a system for the operator. However, the optimal automation system design meant to improve situational awareness is not always realized during operation. Endsley and Kiris (1995) lists three major mechanisms through which automation can directly affect situational awareness: (1) a loss of vigilance and increase in complacency associated with the assumption of a monitoring role; (2) a move from active processor of information to passive recipient of information; and (3) a loss of or change in the type of feedback provided to operators concerning the state of the system (p. 382). In addition to these three mechanisms, a lack of understanding of automation can also negatively influence situational awareness.

Changes in vigilance and complacency associated with monitoring can cause significant reductions in situational awareness. These reductions can be caused by human neglect to monitor system parameters or automation itself, vigilance problems that result in a failed attempt at monitoring or system alerts informing the operator of problems that result in the operator failing to grasp the severity of the problem due to high false alarm rates within the system (Endsley, 1996, p9. 166-167).

Many aviation accidents have been attributed to pilots failing to detect critical automation system changes. "Complacency or over-reliance on automation is one major factor associated with a lack of vigilance in monitoring automation" (Endsley, 1996, p. 167). Complacency can be attributed to pilots placing too much trust in automated systems due to the low failure rates of automated systems. This trust is vital for manufactures producing the automation systems to establish but can lead to pilots diverting their attention away from the automation systems, thus

reducing their situational awareness. The probability of an undetected automation failure due to a lack in situational awareness is increased when automation systems behave reasonably but in an incorrect manner. In contrast to undetected automation failures, monitoring problems are also prevalent in systems producing high false alarm rates. High false alarm rates can produce a lack of trust, and cause pilots to ignore or disable noticeable usual or auditory warning signals or alarms (Endsley, 1996, p. 167).

In addition to vigilance, complacency, and monitoring, the role the operator performs, whether active or passive can negatively affect situational awareness. When actively processing or controlling systems operations, operators tend to have an easier time detecting anomalies and reacting to them. When performing a passive observer role of an automated system, the operator tends to have difficulty determining the need for system intervention and orienting themselves to the current system performance parameters to accomplish such an intervention. "Turning a human operator from a performer into an observer can, in and of itself, negatively affect situational awareness, even if the operator is able to function as an effective monitor, and this can lead to significant problems in taking over during automation failure" (Endsley, 1996, p. 168). Passive processing of information may also inhibit the integration of system information into active working memory. As a result, a monitor may have a lower comprehension of data pertaining to overall system function. This can further cause a more passive approach to decision making regarding system data and an over reliance on manufacture or expert recommendations rather than interpretation and evaluation of actual system performance (Endsley, 1996, pp. 167-168).

Feedback is another mechanism that can directly affect situational awareness. Actions require feedback for appropriate monitoring, error detection, error correction, and for the

operator performing actions to stay engaged with respect to system operation. “When processes are automated, new forms of feedback are created, frequently incorporating more accurate visual displays; yet the fact that information is in a different format may make it harder to assimilate with other information or less salient in a complex environment” (Endsley, 1996, p. 168-169). However, Norman (1990) points out adequate feedback to the human operators is absent far more than it is present, whether the system is a computer operating system, an autopilot or a telephone system (p. 11). Automation designs have in some cases intentionally concealed information from the operator. Lack of feedback prohibits learning of tasks and the way systems respond to various inputs, both of which lead to a reduction in situational awareness. “Without appropriate feedback, people are indeed out of the loop: they may not know if their requests have been received, if the actions are being performed properly or if problems are occurring” (Norman, 1990, p. 11). The elimination or change of system feedback provided to operators, whether intentional or inadvertent during the design process, represents a substantial challenge to operators when it comes to maintaining situational awareness (Norman, 1990, pp. 10-12).

Another major obstacle to achieving situational awareness in relation to automation in aviation is a lack of understanding of automation. This topic was briefly mentioned when discussing the levels of situational awareness failures but is much more complex and requires further explanation. Endsley (1996) notes one of the major impediments to the successful implementation of automation is the difficulty many operators have in understanding automated systems, even when they are attending to them and the automation is working as designed (p. 4).

The inherent complexity of automated systems, poor training, and inadequate interface designs are some of the leading causes of this lack of understanding. The development and sustainment of situational awareness requires a pilot to track a “large quantity of rapidly

changing system parameters, and then integrating them with other parameters, active goals and one's mental model of the system to understand what is happening and project what the system is going to do" (Endsley, 1996, p. 4). This understanding is imperative to permit a pilot to proactively perform as an operator and take actions accordingly to prevent future problems. The problem of understanding becomes more evident as system complexity increases, as automation has done since its inception. Tasks become more complex and demanding, and the system function itself becomes more complex and difficult to understand. With complexity also comes an increase in parameters and information that must be monitored and understood. Comprehension and projection increasingly become more difficult and situational awareness can be lost or become much more difficult to obtain. Continuity in design changes and development are vital to increasing understanding of complex automated systems and allow pilots to gain situational awareness.

Methodology

Study Design

This study is designed as an eleven-year qualitative and quantitative time series analysis of the causal factors of accidents and ensuing fatalities in part 121 and part 135 U.S. civil aviation accidents. A specific focus is given to evaluating the role played by human factor errors in flight accidents and fatalities and whether technological advances and the implementation of automation have affected the number and severity of commercial aviation accidents over the defined time period. Further emphasis is placed on: (1) evaluating the influence and role of pilot training in relation to automation; (2) pilot over-reliance on automation; (3) the merits of intuitive interface design; and (4) the effect crew coordination has on reducing or increasing the rate and severity of aviation accidents and fatalities.

The qualitative section of this analysis strives to determine whether there are practical and/or theoretical underpinnings in the causal analysis of civil aviation accidents and fatalities. In other words, this study will determine whether one factor is more likely to result in an accident or fatality and to what extent certain types of human error are likely to cause an accident that results in fatalities. Furthermore, this study will analyze the role played by the implementation of automation in affecting the number and severity of commercial aviation accidents over the defined time period.

The qualitative analysis splits its focus between the different components of latent and active human errors (defining and analyzing as necessary), as well as other factors that might contribute to aviation accidents and fatalities, and the role played by technological advances in the implementation of automation on aviation accidents.

Data was compiled by reviewing aircraft accident data provided by the U.S. National Transportation Safety Board (NTSB) for the years 2000-2010. This particular time period was chosen for data collection because it was determined that it would provide enough data for robust statistical analysis, and because it was the most recent continuous 11-year period of time when data was available. Perhaps most importantly, the year 2000 will be used as a base for comparison and provide data for an entire year prior to 2001 when commercial aviation traffic was severely affected by the events of September 11. The use of the year 2000 as a base for comparison will help identify any statistical irregularities directly caused by changes in commercial air traffic during 2001 and subsequent years.

The inclusion criteria for this study include civil aviation accidents, as defined by the NTSB, during the above specified time period for part 121 and 135 commercial aircraft. Part 121 refers to scheduled U.S. air carrier operations, while part 135 commercial aircraft are scheduled

or non-scheduled charter and air taxi operations. Data collection is limited to U.S. based commercial air carriers; whether the accident occurred domestically or abroad, the accident is included in this analysis. Aviation incidents and data pertaining to near accidents involving automation technology will not be analyzed as part of this project.

The causal factors used by this study were determined by examining those defined by the NTSB and classifying them accordingly, as well as from information gleaned from a review of relevant literature. Thus, causal factors are defined for the purposes of this study as: (1) human factor errors; (2) environmental factors; (3) mechanical failures; and (4) ground crew errors. An “other” category was introduced into the analysis due to the fact that a number of accidents were categorized by the NTSB in this manner as the accident’s cause could not be entirely attributed to any one of the above mentioned categories or was simply not captured by the defined causal factors – the most prevalent error/failure in the “other” category were accidents involving wildlife, of which bird strikes were most common.

A total of 1,165 accidents (430 – Part 121 accidents and 735 – Part 135 accidents) were examined during the specified time period. The NTSB’s identified causes were recorded and an interpretation of the reports was conducted based on the researcher’s experience in the aviation field to determine the specific human factors involvement and the presence of automation errors. Eight sub-categories of the human factor errors were specified for this report based on the review of relevant literature. For the purpose of this study, human error causal sub-categories are defined as: (1) pilot error not explained or causal factor impossible to determine with information provided on accident report; (2) errors relating to CRM; (3) errors in which fatigue was noted as a contributing factor; (4) errors involving spatial disorientation; (5) situational awareness errors; (6) errors linked to deficiencies in training; (7) system error leading to a mistake due to

insufficient information or faulty information; and (8) errors involving checklists or the organization's standard operating procedures. Detailed exploration into every human factor error was conducted with the intent of discovering relationships between the human factor error with automation or obvious automation errors.

The quantitative section of this analysis will attempt to separate out the automation factor from all other human factor errors to more accurately determine statistical relationships, while the qualitative analysis of this sub-factor will focus on defining automation, discussing optimal automation levels, analyzing the benefits versus shortcomings of automation, and establishing trends in causal factors related to automation technology accidents.

The quantitative analysis attempts to determine whether a significant quantitative relationship exists between the identified causal factors and aviation accidents and fatalities. Statistical regression also attempts to determine the direction and strength of this quantitative relationship, i.e. does an increase in errors among any of the causal factors lead to an increase or decrease in fatalities and to what degree? Furthermore, the regression assists in identifying if any of the causal factors are correlated with each other and to what degree.

Statistical Methodology

Several statistical models were developed to gain an understanding of the quantitative relationships that may exist between the identified causal factors and accidents and fatalities. For the purposes of statistical regression, the following linear regression models were elaborated for each aviation type (part 121 and part 135) and are used as part of this study's analysis:

1. Dependent variable (Y)=Accident rate (total #/flight hours for years 2000-2010)

- a. Independent variables (X)=HF (human factors), ENV (environmental factors), MECH (mechanical factors), GRNDCREW (ground crew errors), & OTHER
2. Dependent variable (Y)=Fatality rate (total #/flight hours for years 2000-2010)
 - a. Independent variables (X) – total # of accidents attributed to each category for years 2000-2010=HF (human factors), ENV (environmental factors), MECH (mechanical factors), GRNDCREW (ground crew errors), & OTHER
 3. Dependent variable (Y)=Accident rate (total #/flight hours for years 2000-2010)
 - a. Independent variable (X) – total # of accidents attributed to automation errors for years 2000-2010=AUTO (automation)
 4. Dependent variable (Y)=Fatality rate (total #/flight hours for years 2000-2010)
 - a. Independent variable (X) – total # of accidents attributed to automation errors for years 2000-2010=AUTO (automation)

A few more statistical models were considered but were eliminated due to the fact that they were not the correct functional form, i.e., the data was not a good fit for the model. For example, the first model chosen was a binary logistic regression format. This was because the data for our chosen dependent variable (either accidents or fatalities) were dummy variables and thus seemed well suited to the binary logistic model. However, this functional form did not account for the flight hours, which if not included, would lead to problems with omitted variables or incorrect assumptions of significance. The solution would be to include this data, however to include this data, the dependent variable would have to be made into a nominal rather than dummy variable, which then made the binary logistic model a poor choice for the data.

In correcting for this error, the linear models were found to be a better fit for the data. This was determined by reviewing the theory more carefully, analyzing the relationship between X and Y, and observing that the non-linear models had biased and inconsistent estimates and overall poor fits.

Theoretical considerations were determined by a review of the relevant literature as well as accident report data. The determination of the variables was especially informed by the literature review, in particular by the various theoretical models of human error classification. Possible problems in identifying the variables included omitted and irrelevant variables – this was overcome by carefully reviewing the literature and by testing the models for reasonable indicators of a good measure of fit.

After the models were developed and tested, and it was determined that the models did not include irrelevant variables nor were there omitted variables, the regressions were examined for violations of the Classical Assumptions. All models were tested for multicollinearity, serial correlation, and heteroskedasticity.

Multicollinearity was a specific concern for this study as many of the identified causal factors of both accidents and fatalities are correlated with one another. For example, a pilot may make a mistake due to poor weather. While the accident may be ultimately classified as due to the pilot's error (HF) and not the weather (ENV), clearly these two variables can affect one another. While test results reflected some multicollinearity, the available solutions would have only made the model worse, so nothing was done to correct the problem; however, its presence (and its effect on results) is noted in the results section of this study.

The models were tested for serial correlation, which is a problem with regressions which observations of the error term are correlated. If serial correlation is impure, omitted variables can

be added to fix the problem, but the functional forms chosen for this study did not have any omitted variables. Another option in the presence of serial correlation is to use the Generalized Least Squares method. In this case, none of the chosen models suffered from serious serial correlation, as revealed by the Durbin-Watson d test.

The models were also tested for heteroskedasticity, which results in the variance of the error term being not constant for all observations. The White test did not reveal a problem with heteroskedasticity for any of the elaborated models; therefore, a Weighted Least Squares approach was not necessary.

An analysis of variance (ANOVA) was also carried out to add specific focus on the statistical relationship between automation and accidents/fatalities. The objective of the ANOVA is to determine if there is a statistically significant difference in the means of the variables to draw conclusions about their statistical relationship. Of specific interest to this study is the relationship between automation and resulting accidents and automation and fatalities. An objective of automation is to reduce accidents and ensuing fatalities, therefore it is hypothesized that automation and accidents/fatalities would be negatively correlated.

Four ANOVA models were developed and run for both parts 121 and 135 resulting in eight sets of output:

1. Dependent variable (Y) = accidents (accident rate for each of the 11 years); Independent variable (X) = automation
2. Dependent variable (Y) = fatalities (fatality rate for each of the 11 years); Independent variable (X) = automation
3. Dependent variable (Y) = accidents attributed to HF causes (accident rate for each of the 11 years); Independent variable (X) = automation

4. Dependent variable (Y) = fatalities attributed to HF causes (fatality rate for each of the 11 years); Independent variable (X) = automation

Limitations

A number of limitations exist that test the validity of the results of this study:

- **The definition of causal factors was subjective.** While the causal factors were developed by reviewing NTSB data, the list of causal factors was finalized by combining several associated sub-categories. This was done partially for the sake of simplicity in data collection, but ultimately to avoid having too many independent variables that were correlated. However, the creation of an “other” category to capture what we determined to be random events was entirely subjective and may have introduced bias into the report.
- **Accident reporting and casual factor determination is by nature subjective.** The NTSB has exclusive and full control over how aviation accidents are investigated and causal factors determined – this may introduce bias if the investigators are not looking beyond the immediate cause of the accident to identify the underlying systemic factors that create conditions under which accidents are more likely to occur. Some of the literature revealed that accidents occur through the combination of multiple latent failures and that each is insufficient to cause the failure itself unless it occurs in combination with other failures. The data reflected this as well, as multiple cases of multicollinearity were observed, revealing that many of the causal factors work together, even if categorized separately. The danger in this study is that statistical results may be a bit biased to indicate a quantitative relationship when one does not exist or it may simply be over-exaggerating the strength of an existing relationship.

- **The statistical analysis was limited in scope to the type of data available**, which was primarily data collected and categorized by the NTSB. While the data itself was comprehensive, the subjective nature of its collection and classification almost entirely introduces bias into statistical results. Furthermore, statistical analyses are useful in demonstrating quantitative relationships but not in proving causation. Thus, while qualitatively it may be shown that automation has been on the increase and accidents and fatalities have decreased over the defined 10-year study period, this supposed causation cannot be proven by statistical analysis. This type of analysis can show a quantitative relationship, but cannot prove that x (automation) causes a decrease in y (accidents/fatalities). This is a limitation of statistical analysis that is not restricted to this study.
- **One way ANOVA only tested the one-way relationship between the variables** when a two-way ANOVA would have been more informative regarding the dynamic relationship that inevitably exists between the independent and dependent variables.
- Automation data was limited in that it was **difficult to accurately determine the type & level of automation within the time and scope of this project.**

Results

Statistical Analysis

A qualitative analysis was carried out on data culled from NTSB reports for the years 2000-2010. Available data included total accidents, total fatalities, and total flight hours for both Part 121 and Part 135 flight operations. Accident reports detailing the probable cause of the accident/fatality were reviewed and probable causes assigned for each accident reported for the observed time period.

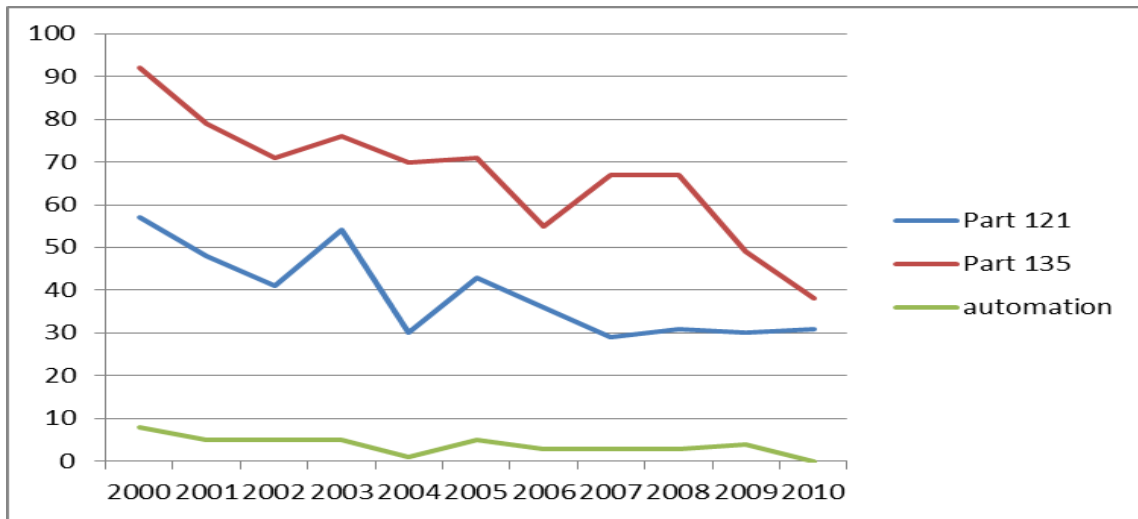


Figure 6
Total Aviation Accidents resulting in Fatalities (Part 121 & Part 135) 2000-2010

For the years 2000-2010 for parts 121 and 135 flight operations, the data included a total of 1,165 accidents, of which 191 were associated with fatalities (figure 1). The vast majority of accidents/fatalities for part 135 flight operations were attributed to human factor causes, while part 121 flight operation accidents/fatalities were more equally distributed among the five probable causes.

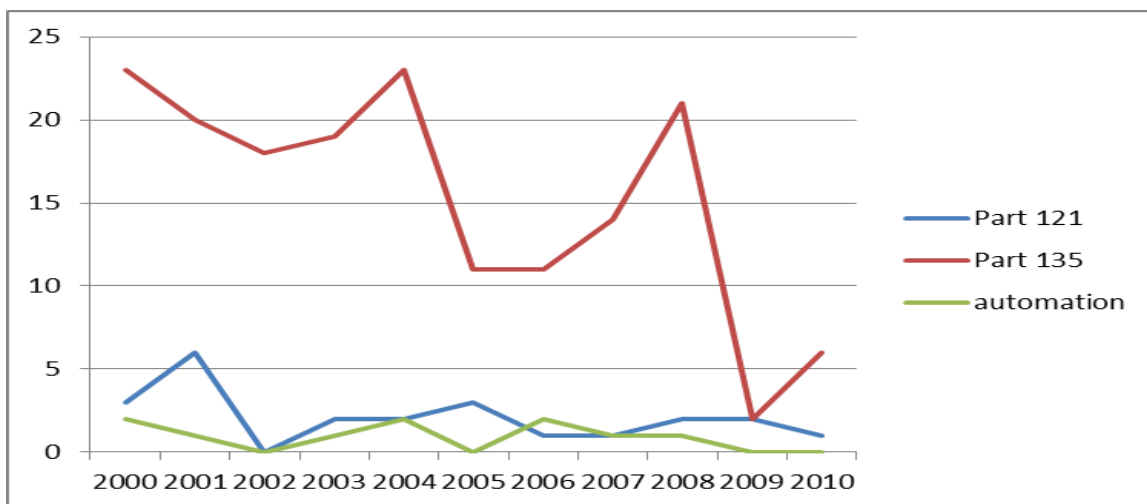


Figure 7
Total Aviation Accidents (Part 121 & Part 135) 2000-2010

An examination of the data reveals the following:

- In relation to this study's hypothesis, which is "there has been a statistical decrease in the number and severity of commercial aviation accidents involving automation from 2000 to 2010," the following was determined:
 - Both the number and severity of commercial aviation accidents have declined over the observed time period (figures 6 & 7).
 - Automation related accidents have also decreased over the observed time period (figures 6 & 7).
 - A statistically significant relationship was observed in an ANOVA exercise between automation and part 135 human factor related fatalities. However, although this was a statistically significant finding, the relationship was not what was expected. Data showed that the two variables have an inverse relationship – when automation increases, so do part 135 fatalities.
 - The remainder of the predictor variables (evolution of pilot training, over reliance on automation, advances in intuitive interface design, and improvements in training and crew coordination) could not be easily quantified within the scope of this project, thus this part of the hypothesis could not be evaluated.
- Accidents and related fatalities are higher for part 135 flight operations, although the gap appears to be closing since 2009 when both declined, with fatalities dropping dramatically.
- Accidents were predominantly attributed to human factor related causes across both types of flight operations, although the distribution among probable causes for part 121 operations was more equally distributed (figures 8 & 9).

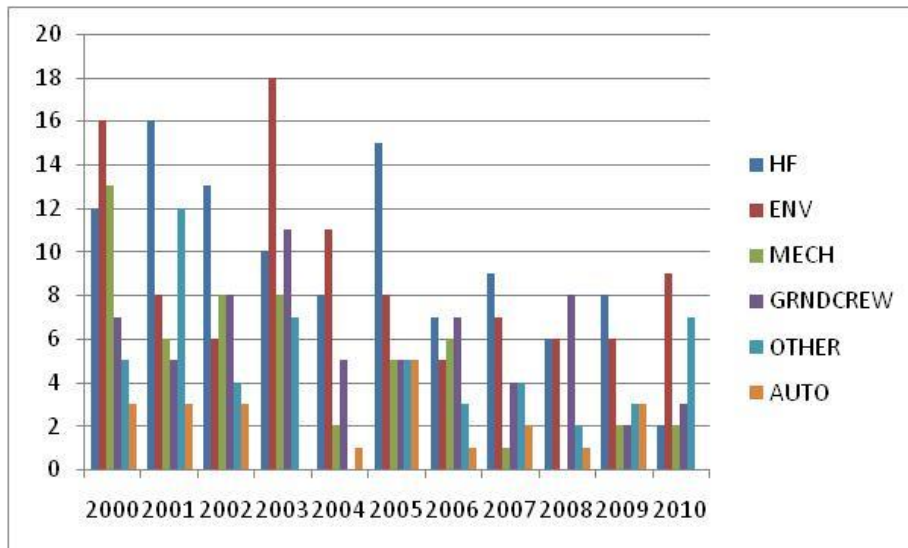


Figure 8
Accidents by Probable Cause – Part 121

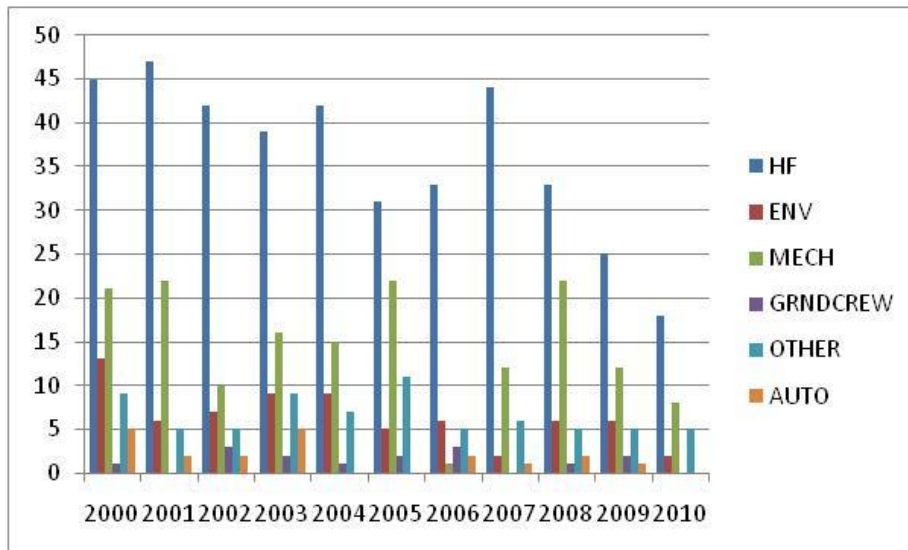


Figure 9
Accidents by Probable Cause – Part 135

Regression

Analysis of regression results reveals that two of the four models are statistically significant. Notably, statistically significant models are ones that test the relationship between the identified causal factors and aviation accidents. The two models that are not statistically significant test the relationship between the identified causal factors and aviation fatalities.

However, regardless of the statistical significance of the model, regression analysis provides valuable information regarding quantitative relationship among the variables, the theoretical underpinnings of the models themselves, and the actual versus expected behavior of the independent variables in relation to one another and to the dependent variable. This section will discuss these areas as well as the individual results of each regression model.

Regression 1 Output: Part 121 Accident Rate

Model

Dependent Variable (y) = Accident Rate

Independent Variable (x) = HF, ENV, MECH, GRNDCREW, OTHER

The r^2 for this model is .975 and the adjusted r^2 is .950, meaning that the overall model fit to the data is exceptionally good (table A3). Ninety-seven percent of the variance in the dependent variable can be explained by the independent variables included in this model. While this is an overall measure of the strength of association between the variables, it does not reflect the extent to which any particular independent variable is associated with the dependent variable – parameter estimate data shows that some of the independent variables are statistically significant. The adjusted r^2 is meant to compensate for extraneous variables, but the fact that the r^2 and adjusted r^2 are not much different is indicative of a very well defined model.

With a p value of .001, the model is statistically significant at both the .05 and .01 levels (table A4). The F ratio is 39.09, which is significantly greater than 1 and thus reveals that the effects observed between the independent and dependent variables is highly unlikely to have happened by chance. Because both the p value and the F ratio are statistically significant, the model significantly improves our ability to predict the outcome variable.

According to p values for each of the independent variables, only ENV (.031), MECH (.009), and OTHER (.030) are statistically different from 0 at the .05 level. Thus, for every unit increase in environmental factors, the part 121 accident rate would increase by 66% (parameter estimate $\beta = .667$); for mechanical factors, the accident rate would increase by 120% ($\beta = 1.2$); and for other factors, the accident rate would increase by 78% ($\beta = .787$) (table A5). It should be noted that the human factor (HF) contribution to accidents in the 11-year period was not statistically significant. If significant, human factor errors would have accounted for 63% (table A2) of the variance in the part 121 accident rate.

Regression analysis revealed that the actual direction of relationships between the independent and dependent variables was as expected; the hypothesized relationship would be positive and each parameter estimate resulted in a positive sign, indicating a positive relationship. In other words, as errors for each probable cause increased, the part 121 accident rate would increase as well.

VIF (variance inflation factor) tests for multicollinearity revealed none – all VIF scores were significantly less than 10 (ranging from a low of 1.3 to a high of 2.4) indicating that multicollinearity for this model is not a concern. Therefore, predictor variables are likely not correlated according to this post hoc test (table A5).

As time series data can lead to autocorrelation of the error term, the Durbin-Watson test was carried out to test for correlated adjacent residuals. Regression assumes independence among error terms – Durbin-Watson tests this assumption. For this model, the Durbin-Watson score is 2.24, which is close to the goal value of 2 indicating no autocorrelation of the error term (table A3).

Regression 2 Output: Part 121 Fatality Rate**Model**

Dependent Variable (y) = Fatality Rate

Independent Variable (x) = HF, ENV, MECH, GRNDCREW, OTHER

The r^2 for this model is .967 and the adjusted r^2 is .884 (table B3). The drop in value from r^2 to adjusted r^2 indicates the possibility that there are extraneous variables in this model.

Eighty-eight percent of the variance in the dependent variable can be explained by the independent variables included in this model.

With a p value of .081, the model is not statistically significant at the .05 level (table B4). The F ratio is 11.644, which is greater than 1 and thus, if the model were statistically significant, would reveal that the effects observed between the independent and dependent variables is highly unlikely to have happened by chance. Because both the p value and the F ratio are not statistically significant, the model does not allow us to predict the outcome variable.

According to p values for each of the independent variables, none are statistically different from 0 at the .05 level.

Regression analysis revealed that the actual direction of relationships between the independent and dependent variables was different from expected; the hypothesized relationship would be positive and several of the parameter estimates resulted in unexpected signs. The actual signs for ENV and GRNDCREW were negative and different from hypothesized. This indicates that for every environmental or ground crew error, the part 121 fatality rate would decrease.

VIF (variance inflation factor) tests for multicollinearity revealed none – all VIF scores were significantly less than 10 (ranging from a low of 1.3 to a high of 3) indicating that multicollinearity for this model is not a concern. However, other measures of collinearity

indicated correlation between GRNDCREW and ENV (.729), MECH and ENV (.714), and GRNDCREW and MECH (.688) (tables B2 and B5).

As time series data can lead to autocorrelation of the error term, the Durbin-Watson test was carried out to test for correlated adjacent residuals. Regression assumes independence among error terms – Durbin-Watson tests this assumption. For this model, the Durbin-Watson score is 3.075, which is significantly above the goal value of 2 indicating possible autocorrelation of the error term (table B3). No corrections were made to improve the model since all other indicators revealed it to be a statistically insignificant model with possible extraneous variables.

Regression 3 Output: Part 135 Accident Rate

Model

Dependent Variable (y) = Accident Rate

Independent Variable (x) = HF, ENV, MECH, GRNDCREW, OTHER

The r^2 for this model is .974 and the adjusted r^2 is .947, meaning that the overall model fit to the data is exceptionally good (table C3). Ninety-seven percent of the variance in the dependent variable can be explained by the independent variables included in this model. While this is an overall measure of the strength of association between the variables, it does not reflect the extent to which any particular independent variable is associated with the dependent variable – parameter estimate data shows that some of the independent variables are statistically significant. The adjusted r^2 is meant to compensate for extraneous variables, but the fact that the r^2 and adjusted r^2 aren't much different is indicative of a very well defined model.

With a p value of .001, the model is statistically significant at both the .05 and .01 levels (table C4). The F ratio is 36.91, which is significantly greater than 1 and thus reveals that the

effects observed between the independent and dependent variables is highly unlikely to have happened by chance. Because both the p value and the F ratio are statistically significant, the model significantly improves our ability to predict the outcome variable.

According to p values for each of the independent variables, only HF (.001) and MECH (.033) are statistically different from 0 at the .05 level. Thus, for every unit increase in human factor errors, the part 135 accident rate would increase by 100% (parameter estimate $\beta = 1.004$); for mechanical errors, accidents would increase by 77% ($\beta = .771$) (table C5).

Regression analysis revealed that the actual direction of relationships between the independent and dependent variables was as expected; the hypothesized relationship would be positive and each parameter estimate resulted in a positive sign, indicating a positive relationship. In other words, as errors for each probable cause increased, the part 135 accident rate would increase as well.

VIF (variance inflation factor) tests for multicollinearity revealed none – all VIF scores were significantly less than 10 (ranging from a low of 1.4 to a high of only 1.8) indicating that multicollinearity for this model is not a concern. Therefore, predictor variables are likely not correlated according to this post hoc test (table C5).

As time series data can lead to autocorrelation of the error term, the Durbin-Watson test was carried out to test for correlated adjacent residuals. Regression assumes independence among error terms – Durbin-Watson tests this assumption. For this model, the Durbin-Watson score is 2.05, which is close to the goal value of 2 indicating no autocorrelation of the error term (table C3).

Regression 4 Output: Part 135 Fatality Rate**Model**

Dependent Variable (y) = Fatality Rate

Independent Variable (x) = HF, ENV, MECH, GRNDCREW, OTHER

The r^2 for this model is .877 and the adjusted r^2 is .769 (table D1). The drop in value from r^2 to adjusted r^2 indicates the possibility that there are extraneous variables in this model.

Eighty-seven percent of the variance in the dependent variable can be explained by the independent variables included in this model.

With a p value of .107, the model is not statistically significant at the .05 level (table D2). The F ratio is 3.32, which is greater than 1 and thus if the model were statistically significant, would reveal that the effects observed between the independent and dependent variables is highly unlikely to have happened by chance. Because both the p value and the F ratio are not statistically significant, the model does not allow us to predict the outcome variable.

According to p values for each of the independent variables, none are statistically different from 0 at the .05 level. Only human factors came even slightly close to being statistically significant with a p value of .086.

Regression analysis revealed that the actual direction of relationships between the independent and dependent variables was different from expected; the hypothesized relationship would be positive and several of the parameter estimates resulted in signs that were not expected. The actual signs for ENV and OTHER were negative and different than hypothesized. This indicates that for every environmental or ground crew error, the part 135 fatality rate would decrease.

VIF (variance inflation factor) tests for multicollinearity were not available for this model due to data constraints – several data points were zero.

As time series data can lead to autocorrelation of the error term, the Durbin-Watson test was carried out to test for correlated adjacent residuals. Regression assumes independence among error terms – Durbin-Watson tests this assumption. For this model, the Durbin-Watson score is 3.97, which is significantly above the goal value of 2 indicating possible autocorrelation of the error term. No corrections were made to improve the model since all other indicators revealed it to be a statistically insignificant model with possible extraneous variables.

ANOVA

An analysis of variance (ANOVA) was conducted to test for statistical significance between the variance in the means of the variables for automation and accidents/fatalities. Due to the fact that there are only two variables in this case, one of which is the dependent (ACCIDENTS or FATALITIES) and the other independent (AUTO), it was determined that the best test of statistical significance would be the ANOVA, rather than a regression. Regression is best suited when there are more than one dependent variable so that the effects between dependent variables can be held constant; in this case, there is only one dependent variable, so the added controls introduced by the various regression models are superfluous and thus not necessary.

ANOVA results showed no statistical significance between the means of any of the variables with the notable exception of the relationship between automation and human factor attributed fatalities in part 135 aviation ($p=.031$, statistically significant at the .05 level). This statistically significant relationship indicates that the variance in the means is not due to chance and is more likely due to the cause and effect between automation and human factor attributed

fatalities. In this case, the data suggests a positive correlation between the two variables.

However, theory suggests a negative correlation, such that as automation increases, the fatality rate would decrease. The results of this ANOVA suggest the opposite – as automation increases, the fatality rate would increase as well. Figure 10 demonstrates the positive, albeit non-linear relationship between automation and human factor attributed fatalities in part 135 aviation operations.

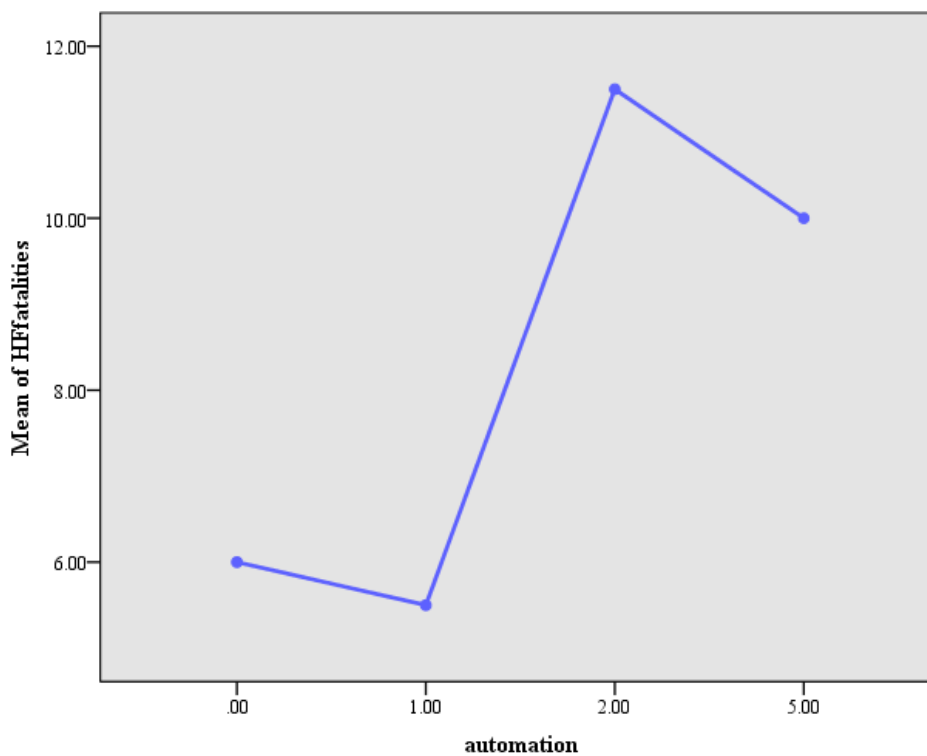


Figure 10

Non-linear Correlation between Part 135 Mean of HF Fatalities and Automation

For the remaining models, the ANOVA results show that the differences in means are likely due to chance rather than the cause and effect between the two variables. However, it should be noted that although not statistically significant, the variables automation and human factor attributed accidents for part 121 aviation show a strong positive linear relationship (figure

11). Although the results are not significant, it should be pointed out that the positive nature of the relationship as detailed in Figure 11 is not expected according to theory. Theory suggests a negative relationship – as automation increases, the accident rate should decrease.

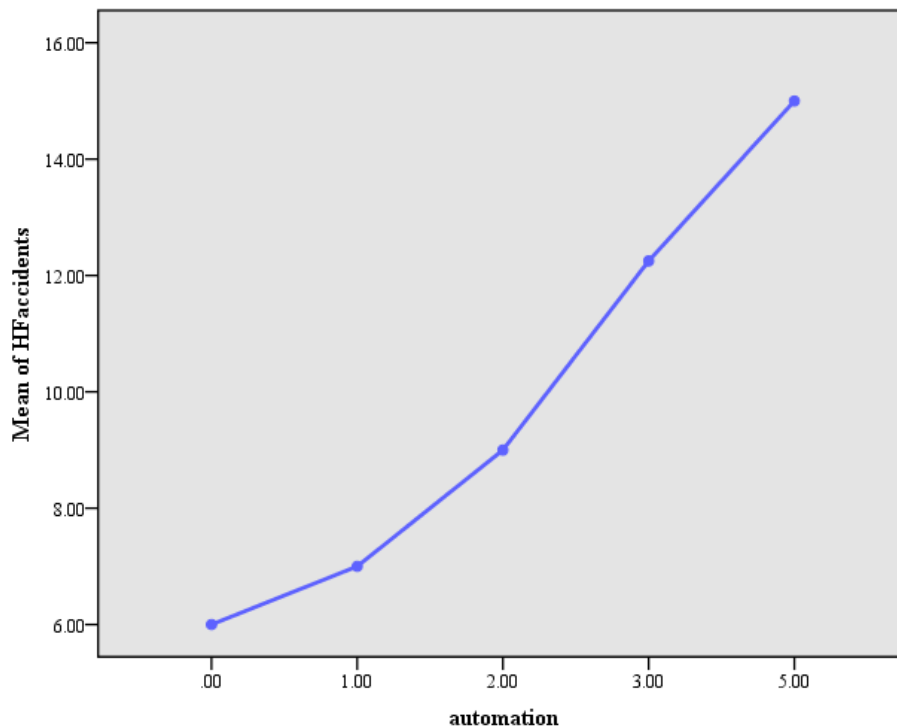


Figure 11
Linear Correlation between Part 121 Mean of HF Accidents and Automation

The output is as follows:

1. Part 121: variance between automation and accidents: $p = .552$ (table E3)
2. Part 121: variance between automation and human factor related accidents: $p = .169$
(table I3)
3. Part 121: variance between automation and fatalities: $p = .819$ (table F3)
4. Part 121: variance between automation and human factor related fatalities: $p = .576$
(table J3)

5. Part 135: variance between automation and accidents: $p = .267$ (table G3)
6. Part 135: variance between automation and human factor attributed accidents: $p = .558$
(table K3)
7. Part 135: variance between automation and fatalities: $p = .272$ (table H3)
8. Part 135: variance between automation and human factor attributed fatalities: $p = .031$
(table L3)

Conclusion

The study's qualitative foundation is a comprehensive literature review, which defined applicable terms based on the project proposal, defined and discussed automation, and provided insight into the evolution of automation technology within the aviation industry. The 10 levels of automation were presented, which revealed a variety of challenges that are present when trying to determine the need for appropriate automation levels in any system. Six prominent automation related errors were discussed in detail, including increased monitoring and vigilance requirements, loss of pilot skills, inappropriate feedback and user interface, workload redistribution, over-reliance on automation and mistrust, and lack of familiarization with systems. The literature review revealed the majority of the most prominent automation errors had a strong relationship with human error.

Because of the strong presence of human error within the review of automation, Reason's Cumulative Effect Theory and the HFACS were examined. The HFACS was examined in detail because it provided a proposed means by which to quantify human error. The review yielded four main levels of error, three of which are labeled as latent failures and one as active. Unsafe acts, preconditions for unsafe acts, unsafe supervision, and organizational influences and their corresponding subcategories produced four additional topics for in-depth review. CRM, fatigue,

spatial disorientation, and situational awareness were selected because of their strong presence and influence on subcategories of unsafe acts, preconditions for unsafe acts, and unsafe supervision.

Due to the nature of this study and its intended purpose, the review of CRM, fatigue, spatial disorientation, and situational awareness was aimed at explaining each of the identified contributors to human error and defining their relationship to automation. A review of CRM provided a brief history discussing the evolution of the six generations of CRM. Factors affecting crew performance were outlined and relationships to CRM's effect on automation were discussed. Fatigue was discussed by explaining the types, effects on performance, and prevention measure available. The review of spatial disorientation provided a detailed explanation of the phenomena and illusion associated with it. The review also yielded prevention techniques as well as its ties to automation technology. Situational awareness was discussed in detail defining the concept, describing the levels of situational awareness, and listing major obstacles to achieving and maintaining good situational awareness.

A quantitative analysis of 2000-2010 parts 121 and 135 aviation operations data revealed that accidents and related fatalities are higher for part 135 flight operations both in sheer number and rates. Additionally, accidents were predominantly attributed to human factor related causes across both types of flight operations.

Regression analysis demonstrated a statistically significant relationship between predictor variables and accidents for both parts 121 and 135 aviation operations. In fact, for every unit increase in environmental factors, the part 121 accident rate would increase by 66% (parameter estimate $\beta = .667$); for mechanical factors, the part 121 accident rate would increase by 120% ($\beta = 1.2$); and for other factors, the part 121 accident rate would increase by 78% ($\beta = .787$) (table

A5). For every unit increase in human factor errors, the part 135 accident rate would increase by 100% (parameter estimate $\beta = 1.004$); for mechanical errors, the part 135 accident rate would increase by 77% ($\beta = .771$) (table C5).

Analysis of variance resulted in only one statistically significant relationship – between automation and human factor attributed fatalities in part 135 aviation ($p=.031$, statistically significant at the .05 level). This statistically significant relationship indicates that the variance in the means is not due to chance and is more likely due to the cause and effect between automation and human factor attributed fatalities.

Analysis of variance showed the variables automation and human factor attributed accidents for part 121 aviation show a strong positive linear relationship. Although the results are not statistically significant, it should be pointed out that the positive nature of the relationship is not expected according to theory.

In relation to this study's hypothesis, which is "there has been a statistical decrease in the number and severity of commercial aviation accidents involving automation from 2000 to 2010" the following was determined: both the number and severity of commercial aviation accidents involving automation decreased over the observed time period, thus disproving the null hypothesis.

Furthermore, this study could not link hypothesized decrease in aviation accidents to the evolution of pilot training in regard to automation, a decrease in over-reliance on automation, advances in intuitive interface design, and improvements in training and utilization of crew coordination because data regarding these factors could not be easily quantified within the scope of this project.

Recommendations

Organizational influences on human error have been extremely difficult to assess historically. Whether the error is due to resource management, organizational climate, or organizational processes, there is a strong need for further development of a classification and quantification system to analyze these influences. The HFACS is a comprehensive and detailed approach, which is well suited for this task. However, without a change in the way accident investigations are conducted these factors will continue to be difficult to ascertain. **Research into the accident investigation procedures and the methodology behind the inclusion or exclusion of possible organizational influences on accidents is recommended.**

Research yielded ten distinct levels of automation in this study. Endsley (1997) identified four generic functions to evaluate optimal automation and human interaction needs. They include monitoring/scanning displays to perceive system status, generating/formulating options or strategies for achieving goals, selecting/deciding on a particular option or strategy, and implementing/carrying out the chosen option. **There is a definite need to develop a comprehensive analysis system to discern the optimal automation levels that can be utilized in the conceptual, design, and production of future automated systems. Detailed research into the four generic functions in conjunction with the ten levels of automation discussed in this study is recommended.**

This study identified six problems with automation technology including increased monitoring and vigilance requirements, loss of pilot skills, inappropriate feedback, workload redistribution, over-reliance on automation and mistrust, and lack of familiarity with automation technology. These six problems are not all encompassing, but when combined with the review of CRM a need for further research regarding training methods and their development was clear.

The nature of CRM and its evolution, which now focuses on TEM, stands as the most widely used apparatus for training in today's aviation industry post initial flight training. As such, **this study recommends further analysis of the way TEM training approaches TEM, and if further development of such training could be developed to be more proactive in nature versus the historical reactive nature of such training.**

In proving this study's hypothesis, human factor attributed accidents emerged as the largest causal factor for the time period specified for both part 121 and part 135 aviation operations. This significant finding provides evidence that **more research is required to ascertain the extent to which human factors influence accident rates, and to further validate this study's classification system of human factors.** Distorted numbers of human factor errors noted during the data gathering phase of this study lend the researcher to believe that some of the predetermined categories to classify human error may be too vague or too encompassing.

The statistical analysis of part 135 fatality rates and automation yielded an unexpected finding. Not all the statistically significant models provided the expected results, but ANOVA showed an inverse relationship compared to what was hypothesized to occur. **The need to determine whether the statistically significant relationship between automation increases and part 135 fatality increases in this study was an anomaly or does indeed exist is important.** Due to limitations of this study previously mentioned in determining some causal factors in part 135, this relationship needs further exploration.

This study operated under the assumption that during the specified time period, automation technology continuously advanced and was more prevalent in both part 121 and part 135 operations from one year to the next. **In order to better determine the effect of**

automation on accident rates and severity there is a need to develop a means to analyze and quantify this assumed increase. Without a means to quantify this factor, significant relationships and patterns can be identified regarding accident rates and severity caused by automation but their significance cannot truly be explained or understood.

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Appendix A

Regression 1 Output: Part 121 Accident Rate

Dependent Variable (y) = Accident Rate

Independent Variable (x) = HF, ENV, MECH, GRNDCREW, OTHER

Table A1

Descriptive Statistics

	Mean	Std. Deviation	N
Accidents	39.0909	10.24163	11
ENV	9.0909	4.27679	11
HF	9.6364	4.12971	11
MECH	4.8182	3.89405	11
GRNDCREW	5.9091	2.58668	11
OTHER	4.7273	3.16515	11

Table A2

Correlations

		Accidents	ENV	HF	MECH	GRNDCREW	OTHER
Pearson Correlation	Accidents	1.000	.701	.632	.901	.582	.550
	ENV	.701	1.000	.127	.572	.471	.216
	HF	.632	.127	1.000	.543	.203	.420
	MECH	.901	.572	.543	1.000	.505	.336
	GRNDCREW	.582	.471	.203	.505	1.000	.021
	OTHER	.550	.216	.420	.336	.021	1.000
Sig. (1-tailed)	Accidents	.	.008	.018	.000	.030	.040
	ENV	.008	.	.355	.033	.072	.262
	HF	.018	.355	.	.042	.275	.099
	MECH	.000	.033	.042	.	.057	.156
	GRNDCREW	.030	.072	.275	.057	.	.475
	OTHER	.040	.262	.099	.156	.475	.
N	Accidents	11	11	11	11	11	11
	ENV	11	11	11	11	11	11
	HF	11	11	11	11	11	11
	MECH	11	11	11	11	11	11
	GRNDCREW	11	11	11	11	11	11
	OTHER	11	11	11	11	11	11

Table A3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.987	.975	.950	2.28756	.975	39.089	5	5	.001	2.248

Table A4

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1022.745	5	204.549	39.089	.001
	Residual	26.165	5	5.233		
	Total	1048.909	10			

Table A5

Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF	
1	Constant	14.443	2.785		5.187	.004	7.285	21.601					
	ENV	.667	.223	.279	2.986	.031	.093	1.242	.701	.800	.211	.573	1.746
	HF	.524	.229	.211	2.291	.071	-.064	1.111	.632	.716	.162	.588	1.702
	MECH	1.206	.291	.459	4.146	.009	.458	1.954	.901	.880	.293	.408	2.453
	GRND CREW	.678	.342	.171	1.981	.105	-.202	1.557	.582	.663	.140	.668	1.497
	OTHER	.787	.261	.243	3.009	.030	.115	1.459	.550	.803	.212	.764	1.309

Table A6

Coefficient Correlations

Model		OTHER	GRNDCREW	HF	ENV	MECH
1	OTHER	1.000	.198	-.320	-.167	-.098
	GRNDCREW	.198	1.000	-.034	-.266	-.299
	HF	-.320	-.034	1.000	.288	-.499
	ENV	-.167	-.266	.288	1.000	-.466
	MECH	-.098	-.299	-.499	-.466	1.000
Covariances	OTHER	.068	.018	-.019	-.010	-.007
	GRNDCREW	.018	.117	-.003	-.020	-.030
	HF	-.019	-.003	.052	.015	-.033
	ENV	-.010	-.020	.015	.050	-.030
	MECH	-.007	-.030	-.033	-.030	.085

Table A7

Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions					
				(Constant)	ENV	HF	MECH	GRND CREW	OTHER
1	1	5.295	1.000	.00	.00	.00	.00	.00	.01
	2	.257	4.535	.00	.03	.01	.10	.05	.52
	3	.218	4.930	.07	.01	.00	.39	.05	.07
	4	.124	6.530	.01	.29	.33	.01	.00	.20
	5	.070	8.670	.04	.33	.09	.00	.79	.21
	6	.035	12.371	.87	.34	.57	.50	.11	.00

Table A8

Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	28.5834	55.7626	39.0909	10.11308	11
Residual	-2.47279	2.41659	.00000	1.61755	11
Std. Predicted Value	-1.039	1.649	.000	1.000	11
Std. Residual	-1.081	1.056	.000	.707	11

Appendix B

Regression 2 Output: Part 121 Fatalities

Dependent Variable (y) = Fatality Rate

Independent Variable (x) = HF, ENV, MECH, GRNDCREW, OTHER

Table B1

Descriptive Statistics

	Mean	Std. Deviation	N
FATALITY	2.375	1.68502	8
HF	9.875	4.51782	8
ENV	9.625	4.74906	8
MECH	5.375	3.92565	8
GRNDCREW	5.5	2.82843	8
OTHER	5.75	2.96407	8

Table B2

Correlations

		FATALITY	HF	ENV	MECH	GRNDCREW	OTHER
Pearson Correlation	FATALITY	1.000	.814	.109	.364	.045	.765
	HF	.814	1.000	.157	.430	.240	.403
	ENV	.109	.157	1.000	.714	.729	.236
	MECH	.364	.430	.714	1.000	.688	.157
	GRNDCREW	.045	.240	.729	.688	1.000	.136
	OTHER	.765	.403	.236	.157	.136	1.000
Sig. (1-tailed)	FATALITY	.	.007	.398	.187	.458	.013
	HF	.007	.	.355	.144	.283	.161
	ENV	.398	.355	.	.023	.020	.287
	MECH	.187	.144	.023	.	.030	.356
	GRNDCREW	.458	.283	.020	.030	.	.374
	OTHER	.013	.161	.287	.356	.374	.
N	FATALITY	8	8	8	8	8	8
	HF	8	8	8	8	8	8
	ENV	8	8	8	8	8	8
	MECH	8	8	8	8	8	8
	GRNDCREW	8	8	8	8	8	8
	OTHER	8	8	8	8	8	8

Table B3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.983	.967	.884	.57449	.967	11.644	5	2	.081	3.075

Table B4

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	19.215	5	3.843	11.644	.081
Residual	.660	2	.330		
Total	19.875	7			

Table B5

Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1 Constant	-.772	.710		-1.086	.391	-3.828	2.285					
HF	.195	.061	.523	3.193	.086	-.068	.458	.814	.914	.411	.620	1.613
ENV	-.052	.079	-.148	-.662	.576	-.394	.289	.109	-.424	-.085	.333	3.007
MECH	.156	.095	.362	1.632	.244	-.255	.566	.364	.756	.210	.337	2.969
GRND CREW	-.179	.120	-.301	-1.492	.274	-.696	.337	.045	-.726	-.192	.409	2.445
OTHER	.326	.084	.574	3.880	.060	-.036	.688	.765	.940	.500	.759	1.317

Table B6

Coefficient Correlations

Model		OTHER	GRNDCREW	HF	MECH	ENV
1	OTHER	1.000	.071	-.440	.204	-.297
	GRNDCREW	.071	1.000	-.058	-.283	-.461
	HF	-.440	-.058	1.000	-.466	.322
	MECH	.204	-.283	-.466	1.000	-.501
	ENV	-.297	-.461	.322	-.501	1.000
Covariances	OTHER	.007	.001	-.002	.002	-.002
	GRNDCREW	.001	.014	.000	-.003	-.004
	HF	-.002	.000	.004	-.003	.002
	MECH	.002	-.003	-.003	.009	-.004
	ENV	-.002	-.004	.002	-.004	.006

Table B7

Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions					
				(Constant)	HF	ENV	MECH	GRNDCREW	OTHER
1	1	5.401	1.000	.00	.00	.00	.00	.00	.00
	2	.284	4.361	.02	.03	.02	.12	.03	.16
	3	.127	6.519	.04	.33	.08	.18	.06	.02
	4	.100	7.350	.27	.08	.01	.08	.03	.66
	5	.053	10.056	.31	.07	.11	.17	.82	.03
	6	.035	12.471	.36	.48	.79	.45	.07	.13

Table B8

Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.9888	5.8796	2.3750	1.65680	8
Residual	-.35949	.59552	.00000	.30708	8
Std. Predicted Value	-.837	2.115	.000	1.000	8
Std. Residual	-.626	1.037	.000	.535	8

Appendix C

Regression 3 Output: Part 135 Accident Rate

Dependent Variable (y) = Accident Rate

Independent Variable (x) = HF, ENV, MECH, GRNDCREW, OTHER

Table C1

Descriptive Statistics

	Mean	Std. Deviation	N
Accidents	66.8182	14.83117	11
HF	36.2727	9.13336	11
ENV	6.4545	3.14209	11
MECH	15.3636	5.57266	11
GRNDCREW	1.3636	1.12006	11
OTHER	6.5455	2.16165	11

Table C2

Correlations

		accidents	HF	ENV	MECH	GRNDCREW	OTHER
Pearson Correlation	Accidents	1.000	.858	.704	.703	-.020	.527
	HF	.858	1.000	.487	.393	-.089	.169
	ENV	.704	.487	1.000	.407	.289	.416
	MECH	.703	.393	.407	1.000	-.248	.505
	GRNDCREW	-.020	-.089	.289	-.248	1.000	.116
	OTHER	.527	.169	.416	.505	.116	1.000
Sig. (1-tailed)	Accidents	.	.000	.008	.008	.477	.048
	HF	.000	.	.065	.116	.397	.310
	ENV	.008	.065	.	.107	.194	.101
	MECH	.008	.116	.107	.	.231	.057
	GRNDCREW	.477	.397	.194	.231	.	.367
	OTHER	.048	.310	.101	.057	.367	.
N	Accidents	11	11	11	11	11	11
	HF	11	11	11	11	11	11
	ENV	11	11	11	11	11	11
	MECH	11	11	11	11	11	11
	GRNDCREW	11	11	11	11	11	11
	OTHER	11	11	11	11	11	11

Table C3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.987	.974	.947	3.40669	.974	36.907	5	5	.001	2.057

Table C4

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	2141.609	5	428.322	36.907	.001
1 Residual	58.028	5	11.606		
Total	2199.636	10			

Table C5

Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1 Constant	3.435	5.604		.613	.567	-10.969	17.840					
1 HF	1.004	.143	.619	7.019	.001	.637	1.372	.858	.953	.510	.679	1.472
1 ENV	.931	.472	.197	1.971	.106	-.283	2.145	.704	.661	.143	.527	1.898
1 MECH	.771	.264	.290	2.917	.033	.092	1.451	.703	.794	.212	.535	1.870
1 GRND CREW	.367	1.145	.028	.320	.762	-2.576	3.309	-.020	.142	.023	.706	1.416
1 OTHER	1.312	.616	.191	2.130	.086	-.271	2.896	.527	.690	.155	.654	1.528

Table C6

Coefficient Correlations

Model		OTHER	GRNDCREW	HF	MECH	ENV
1	OTHER	1.000	-.172	.125	-.455	-.201
	GRNDCREW	-.172	1.000	.170	.408	-.423
	Correlations HF	.125	.170	1.000	-.188	-.442
	MECH	-.455	.408	-.188	1.000	-.255
	ENV	-.201	-.423	-.442	-.255	1.000
Covariances	OTHER	.380	-.121	.011	-.074	-.058
	GRNDCREW	-.121	1.310	.028	.123	-.229
	HF	.011	.028	.020	-.007	-.030
	MECH	-.074	.123	-.007	.070	-.032
	ENV	-.058	-.229	-.030	-.032	.223

Table C7

Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions					
				(Constant)	HF	ENV	MECH	GRND CREW	OTHER
1	1	5.406	1.000	.00	.00	.00	.00	.01	.00
	2	.367	3.838	.00	.00	.00	.02	.59	.00
	3	.102	7.275	.06	.00	.69	.00	.03	.02
	4	.067	8.967	.05	.20	.00	.08	.01	.37
	5	.039	11.817	.03	.01	.05	.90	.26	.45
	6	.019	16.806	.86	.78	.25	.00	.10	.15

Table C8

Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	36.1090	89.1128	66.8182	14.63424	11
Residual Std.	-5.12344	3.48569	.00000	2.40889	11
Predicted Value	-2.098	1.523	.000	1.000	11
Residual Std.	-1.504	1.023	.000	.707	11

Appendix D

Regression 4 Output: Part 135 Fatalities

Dependent Variable (y) = Fatality Rate

Independent Variable (x) = HF, ENV, MECH, GRNDCREW, OTHER

Table D1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.877	.769	.537	4.79106

Table D2

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	381.411	5	76.282	3.323	.107
1 Residual	114.771	5	22.954		
Total	496.182	10			

Table D3

Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	-6.040	7.881		-.766	.478
1 HF	.430	.201	.557	2.136	.086
1 ENV	.778	.664	.347	1.172	.294
1 MECH	.258	.372	.204	.693	.519
1 GRNDCREW	-.813	1.610	-.129	-.505	.635
1 OTHER	-.329	.866	-.101	-.379	.720

Table D4

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
HF	11	18.00	47.00	36.2727	9.13336
ENV	11	2.00	13.00	6.4545	3.14209
MECH	11	8.00	22.00	15.3636	5.57266
GRNDCREW	11	.00	3.00	1.3636	1.12006
OTHER	11	5.00	11.00	6.5455	2.16165
Valid N (listwise)	11				

Appendix E

ANOVA 1 Output: Part 121 Automation Accidents

Dependent Variable (y) = Accident Rate
 Independent Variable (x) = Automation

Table E1

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
					Lower Bound	Upper Bound			
.00	2	42.5000	16.26346	11.50000	-103.6214	188.6214	31.00	54.00	
1.00	3	32.3333	3.21455	1.85592	24.3479	40.3187	30.00	36.00	
2.00	1	29.0000	29.00	29.00	
3.00	4	44.0000	11.40175	5.70088	25.8573	62.1427	30.00	57.00	
5.00	1	43.0000	43.00	43.00	
Total	11	39.0909	10.24163	3.08797	32.2105	45.9713	29.00	57.00	
Model			10.60791	3.19841	31.2647	46.9171			
Fixed Effects				3.19841	30.2107	47.9711			
Random Effects									-9.33395

Table E2

Test of Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
3.226	2	6	.112

Table E3

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	373.742	4	93.436	.830	.552
Within Groups	675.167	6	112.528		
Total	1048.909	10			

Appendix F

ANOVA 2 Output: Part 121 Automation Fatalities

Dependent Variable (y) = Fatality Rate
 Independent Variable (x) = Automation

Table F1

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
					Lower Bound	Upper Bound			
.00	2	1.5000	.70711	.50000	-4.8531	7.8531	1.00	2.00	
1.00	3	1.6667	.57735	.33333	.2324	3.1009	1.00	2.00	
2.00	1	1.0000	1.00	1.00	
3.00	4	2.7500	2.50000	1.25000	-1.2281	6.7281	.00	6.00	
5.00	1	3.0000	3.00	3.00	
Total	11	2.0909	1.57826	.47586	1.0306	3.1512	.00	6.00	
Model			1.82193	.54933	.7467	3.4351			
Fixed Effects				.54933	.5657	3.6161			-1.01265
Random Effects									

Table F2

Test of Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
1.672	2	6	.265

Table F3

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.992	4	1.248	.376	.819
Within Groups	19.917	6	3.319		
Total	24.909	10			

Appendix G

ANOVA 3 Output: Part 135 Automation Accidents

Dependent Variable (y) = Accident Rate

Independent Variable (x) = Automation

Table G1

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
					Lower Bound	Upper Bound			
.00	3	59.6667	18.77054	10.83718	13.0380	106.2953	38.00	71.00	
1.00	2	58.0000	12.72792	9.00000	-56.3558	172.3558	49.00	67.00	
2.00	4	68.0000	10.00000	5.00000	52.0878	83.9122	55.00	79.00	
5.00	2	84.0000	11.31371	8.00000	-17.6496	185.6496	76.00	92.00	
Total	11	66.8182	14.83117	4.47177	56.8545	76.7819	38.00	92.00	
Model	Fixed Effects		13.59972	4.10047	57.1221	76.5143			
	Random Effects			5.36186	49.7544	83.8820			43.76407

Table G2

Test of Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
1.319	3	7	.342

Table G3

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	904.970	3	301.657	1.631	.267
Within Groups	1294.667	7	184.952		
Total	2199.636	10			

Appendix H

ANOVA 4 Output: Part 135 Automation Fatalities

Dependent Variable (y) = Fatality Rate
 Independent Variable (x) = Automation

Table H1

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
					Lower Bound	Upper Bound			
.00	3	13.3333	8.73689	5.04425	-8.3703	35.0370	6.00	23.00	
1.00	2	8.0000	8.48528	6.00000	-68.2372	84.2372	2.00	14.00	
2.00	4	17.5000	4.50925	2.25462	10.3248	24.6752	11.00	21.00	
5.00	2	21.0000	2.82843	2.00000	-4.4124	46.4124	19.00	23.00	
Total	11	15.2727	7.04402	2.12385	10.5405	20.0050	2.00	23.00	
Model			6.47707	1.95291	10.6548	19.8906			9.58225
Fixed Effects				2.53519	7.2046	23.3408			
Random Effects									

Table H2

Test of Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
1.718	3	7	.250

Table H3

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	202.515	3	67.505	1.609	.272
Within Groups	293.667	7	41.952		
Total	496.182	10			

Appendix I

ANOVA 5 Output: Part 121 Automation Human Factors Accidents

Dependent Variable (y) = Accident Rate for all Human Factor attributed accidents

Independent Variable (x) = Automation

Table I1

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
					Lower Bound	Upper Bound			
.00	2	6.0000	5.65685	4.00000	-44.8248	56.8248	2.00	10.00	
1.00	3	7.0000	1.00000	.57735	4.5159	9.4841	6.00	8.00	
2.00	1	9.0000	9.00	9.00	
3.00	4	12.2500	3.30404	1.65202	6.9925	17.5075	8.00	16.00	
5.00	1	15.0000	15.00	15.00	
Total	11	9.6364	4.12971	1.24516	6.8620	12.4107	2.00	16.00	
Model			3.33542	1.00567	7.1756	12.0971			
Random Effects				1.69354	4.9343	14.3384			

Table I2

Test of Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
3.070	2	6	.121

Table I3

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	103.795	4	25.949	2.332	.169
Within Groups	66.750	6	11.125		
Total	170.545	10			

Appendix J

ANOVA 6 Output: Part 121 Automation Human Factors Fatalities

Dependent Variable (y) = Fatality Rate for all Human Factor attributed fatalities

Independent Variable (x) = Automation

Table J1

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
					Lower Bound	Upper Bound			
.00	2	.0000	.00000	.00000	.0000	.0000	.00	.00	
1.00	3	1.0000	1.00000	.57735	-1.4841	3.4841	.00	2.00	
2.00	1	1.0000	1.00	1.00	
3.00	4	.7500	.50000	.25000	-.0456	1.5456	.00	1.00	
5.00	1	1.0000	1.00	1.00	
Total	11	.7273	.64667	.19498	.2928	1.1617	.00	2.00	
Model			.67700	.20412	.2278	1.2267			
Fixed Effects				.20412	.1605	1.2940			
Random Effects									-.04907

Table J2

Test of Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
1.878	2	6	.233

Table J3

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.432	4	.358	.781	.576
Within Groups	2.750	6	.458		
Total	4.182	10			

Appendix K

ANOVA 7 Output: Part 135 Automation Human Factors Accidents

Dependent Variable (y) = Accident Rate for all Human Factor attributed accidents

Independent Variable (x) = Automation

Table K1

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
					Lower Bound	Upper Bound			
.00	3	30.3333	12.01388	6.93622	.4892	60.1775	18.00	42.00	
1.00	2	34.5000	13.43503	9.50000	-86.2089	155.2089	25.00	44.00	
2.00	4	38.7500	6.94622	3.47311	27.6970	49.8030	33.00	47.00	
5.00	2	42.0000	4.24264	3.00000	3.8814	80.1186	39.00	45.00	
Total	11	36.2727	9.13336	2.75381	30.1369	42.4086	18.00	47.00	
Model			9.50125	2.86474	29.4987	43.0468			
Fixed Effects				2.86474	27.1559	45.3896			
Random Effects									-8.56953

Table K2

Test of Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
1.270	3	7	.356

Table K3

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	202.265	3	67.422	.747	.558
Within Groups	631.917	7	90.274		
Total	834.182	10			

Appendix L

ANOVA 8 Output: Part 135 Automation Human Factors Fatalities

Dependent Variable (y) = Fatality Rate for all Human Factor attributed fatalities

Independent Variable (x) = Automation

Table L1

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
					Lower Bound	Upper Bound			
.00	3	6.0000	6.08276	3.51188	-9.1104	21.1104	2.00	13.00	
1.00	2	5.5000	4.94975	3.50000	-38.9717	49.9717	2.00	9.00	
2.00	4	11.5000	2.38048	1.19024	7.7121	15.2879	8.00	13.00	
5.00	2	10.0000	.00000	.00000	10.0000	10.0000	10.00	10.00	
Total	11	8.6364	4.38800	1.32303	5.6885	11.5843	2.00	13.00	
Model			4.06202	1.22474	5.7403	11.5324			
Fixed Effects									
Random Effects				1.56175	3.6662	13.6065			3.44318

Table L2

Test of Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
5.358	3	7	.228

Table L3

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	77.045	3	25.682	15.56	.031
Within Groups	115.500	7	16.500		
Total	192.545	10			