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The Effect of Pilot and Air Traffic Control Experiences & Automation Management Strategies on UAS Mission Task Performance

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THE EFFECT OF PILOT AND AIR TRAFFIC CONTROL EXPERIENCES & AUTOMATION MANAGEMENT STRATEGIES ON UAS MISSION TASK PERFORMANCE

by

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This thesis was prepared under the direction of the candidate's thesis committee chair, Dr. Dahai Liu, Ph.D., Department of Human Factors & Systems, and has been approved by members of the thesis committee. It was submitted to the Department of Human Factors & Systems and has been accepted in partial fulfillment of the requirements for the degree of Master of Science in Human Factors & Systems.

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Abstract

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Unmanned aircraft are relied on now more than ever to save lives and support the troops in the recent Operation Enduring Freedom and Operation Iraqi Freedom. The demands for UAS capabilities are rapidly increasing in the civilian sector. However, UAS operations will not be carried out in the NAS until safety concerns are alleviated. Among these concerns is determining the appropriate level of automation in conjunction with a suitable pilot who exhibits the necessary knowledge, skills, and abilities to safely operate these systems.

This research examined two levels of automation: Management by Consent (MBC) and Management by Exception (MBE). User experiences were also analyzed in conjunction with both levels of automation while operating an unmanned aircraft simulator. The user experiences encompass three individual groups: Pilots, ATC, and Human Factors. Performance, workload, and situation awareness data were examined, but did not show any significant differences among the groups. Shortfalls and constraints are heavily examined to help pave the wave for future research.

Acknowledgements

I would like to dedicate this research to my son Triston who gave me the inspiration, motivation, and reason to succeed. The countless times that he sat on my shoulders holding my eyelids open as I read through journal articles and typed away on this report will always be remembered and cherished. It is his hugs, his smiles, and his laughs that give me all the reason to continue on.

I want to express my gratitude to my thesis committee who made this possible. I could not have ended up with a better committee. Dr. Liu provided me with the insight and encouragement to conduct the thesis quickly and efficiently. He provided alternative solutions to meet my goals when it appeared that none existed. Dr. Doherty continuously offered a wealth of information and foresight necessary for me to meet my overall objectives. His suggestions and insight were invaluable throughout the entire program. Dr. Macchiarella responded quickly in a time of urgency. His presence on the committee enabled the research to progress in a timely manner, and his expertise provided real-world insight into UAS operations.

This thesis would not have been possible without the patience and understanding of my wife, Andrea. She managed to endure the inevitable stressful times of 'student living', and accepted the numerous all-nighters I spent working on this thesis. When I was tired, frustrated, and ready to give up, she convinced me to keep going. Thank you.

Most importantly, I would like to thank God for keeping me alive and sane despite all the rigors throughout the past 2 years. It was an extremely tough run, but it has finally come to an end.

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List of Abbreviations

AC	Advisory Circulars
AD	Airworthiness Directives
ADS-B	Automatic Dependent Surveillance-Broadcast
AFRL	Air Force Research Laboratory
AIM	Airman's Information Manual
ASTM	American Society for Testing and Material Standards
ATC	Air Traffic Control
CFR	Code of Federal Regulations
COA	Certificate of Authorization
DSA	Detect, Sense, and Avoid
ELOS	Equivalent Level of Safety
FAA	Federal Aviation Administration
FAR	Federal Aviation Regulations
GA	General Aviation
ICAO	International Civil Aviation Organization
IFR	Instrument Flight Rules
NAS	National Airspace
NASA	National Aeronautics and Space Administration
NextGEN	Next Generation Air Transport System
ROA	Remotely Operator Aircraft
RTCA	Radio Technical Commission for Aeronautics
SWaP	Size, Weight, and Power
TSO	Technical Standard Order
UAS	Unmanned Aircraft System(s)
VFR	Visual Flight Rules

Glossary of Terms

The following definitions are provided by the Federal Aviation Administration and ASTM International:

Airworthiness

For the UAS to be considered airworthy, both the aircraft and all of the other associated support equipment of the UAS must be in a condition for safe operation. If any element of the systems is not in condition for safe operation, then the unmanned aircraft would not be considered airworthy.

Automated

The automatic performance of scripted action

Autonomy

The ability of the machine to interpret its environment and make decision that result in unscripted actions.

Chase Aircraft

A manned aircraft flying in close proximity to an unmanned aircraft that carries, in addition to the pilot in command (PIC) of the aircraft, a qualified visual observer.

Control station

A system of computers and other equipment in a designated operating area that the pilot and other crewmembers use to communicate and fly the unmanned aircraft and to operate its sensors (if any).

Fully autonomous

Mode of control of a UAS where the UAS is expected to execute its mission, within the pre-programmed scope , with only monitoring from the pilot-in-command. As a descriptor for *mode of control*, this term includes: (1) fully automatic operation, (2) autonomous functions (like takeoff, landing, or collision avoidance), (3) "intelligent" fully autonomous operation.

Line of sight

Direct, point-to-point contact between a transmitter and receiver.

Lost link

A situation where the control station has lost either or both of the uplink and downlink contact with the unmanned aircraft and the pilot can no longer affect or monitor, or both, the aircraft's flight.

Mode of control

Means the pilot uses to direct the activity of the UAS. There are two modes of control: semi-autonomous and remote control. A UAS may use different modes of control in different phases of flight.

Operator

Means any person who causes or authorizes the operation of an aircraft, such as the owner, lessee, or bailee of an aircraft. Also, the entity responsible for compliance with airworthiness and continuing airworthiness requirements.

Pilot in Command

The person who has final authority and responsibility for the operation and safety of flight, has been designated as pilot in command before or during the flight, and holds the appropriate category, class, and type rating, if appropriate, for the conduct of the flight. The responsibility and authority of the pilot in command as described by 14 CFR 91.3, Responsibility and Authority of the Pilot in Command, apply to the unmanned aircraft PIC. The pilot in command position may rotate duties as necessary with equally qualified pilots. The individual designated as PIC may change during flight.

Semi-autonomous

Mode of control of a UAS where the pilot executes changes and conducts the mission through a flight management system interface. Without this input, the UAS will perform pre-programmed automatic operations. This can, but might not, include some fully autonomous functions (like takeoff, landing, and collisions avoidance)

Unmanned Aircraft

A device used or intended to be used for flight in the air that has no onboard pilot. This includes all classes of airplanes, helicopters, airships, and translational lift aircraft that have no onboard pilot. Unmanned aircraft are understood to include only those aircraft controllable in three axes and therefore, exclude traditional balloons

Unmanned Aircraft System

Airplane, airship, powered lift, or rotorcraft that operates with the pilot in command off-board, for purposes other than sport of recreation, also known as unmanned aerial vehicle. UASs are designed to be recovered and reused. A UAS system includes all parts of the system (data-link, control station, and so forth) required to operate the aircraft. The plural of UAS is UASs.

Visual Line-of-Sight

A method of control and collision avoidance that refers to the pilot or observer directly viewing the unmanned aircraft with human eyesight. Corrective lenses (spectacles or contact lenses) may be used by the pilot or visual observer. Aids to vision, such as binoculars, field glasses, or telephoto television may be employed as long as their field of view does not adversely affect the surveillance task.

Visual Observer

A trained person who assists the unmanned aircraft pilot in the duties associated with collision avoidance. This includes, but is not limited to, avoidance of other traffic, clouds, obstructions and terrain.

(AIR-160, 2008; ASTM F-2395-07, 2007)

Introduction

The crucial issue is the assimilation of the relevant sensory inputs, the processing of information pertinent to specified user goals, and the translation of the user's subsequent decisions into effective action. The fundamental barrier to success in this realm is not a technological one but a user-centered one.

- Oron-Gilad, Chen, and Hancock, 2006

Unmanned Aircraft Systems (UASs) are on the verge of taking flight alongside manned aircraft in the national airspace system (NAS). These unmanned systems have demonstrated their true potential through military endeavors, and their wide range of capabilities has inspired civilian agencies to harness the benefits that these systems provide. UAS has great potential to change the aviation arena forever, but special attention must be made to safety concerns associated with separating the pilot from the unmanned aircraft. The intent of this thesis is to analyze how the human is safely integrated into this highly automated and very complex system.

Currently, there is no universally supported definition for modern-day UASs. The Department of Defense (DoD) defines these systems as, "*A powered, aerial vehicle that does not carry a human operator, uses aerodynamic forces to provide vehicle lift, can fly autonomously or be piloted remotely, can be expendable or recoverable, and can carry a lethal or non-lethal payload. Ballistic or semi ballistic vehicles, cruise missiles, and artillery projectiles are not considered unmanned aerial vehicles*" (Department of Defense, 2005). The FAA defines an UAS as an: "*Airplane, airship, powered lift, or rotorcraft that operates with the pilot in command off-board, for purposes other than sport of recreation, also known as unmanned aerial vehicle. UASs are designed to be recovered and reused. A UAS system includes all parts of the system (data-link, control station, and so forth) required to operate the aircraft. The plural of UAS is UASs.*" In either case, a pilot is not co-located within the flying component of the system. This creates several human factors concerns regarding how the pilot is then integrated into the system to maintain adequate control (Hottman & Sortland, 2006).

Of primary importance is the skill-set required on behalf of the pilot to safely and effectively fly the unmanned aircraft from a distance. The Federal Aviation Administration (FAA) has developed a number of certification requirements that must be met in order to fly manned aircraft, or to monitor and direct aircraft as an air traffic controller (ATC). Certification requirements for pilots of unmanned aircraft have yet to be developed and little research has been done to evaluate the appropriate knowledge, skills, and abilities (KSAs) that an UAS pilot should possess (Williams, 2005).

A full understanding of the three-dimensional aspect of the unmanned aircraft in the airspace cannot occur without prior experience in the airspace. So, it is logical to suggest that conventional pilots of manned aircraft are comprised with the fundamental KSAs necessary to develop an accurate mental representation of the unmanned aircrafts current status. However, research that assessed the applicability of pilot KSAs applied to UAS operations are rare and has arrived at conflicting conclusions (McCarley & Wickens, 2005; Tirre, 1998; Flach, 1998). Research that analyzes the transfer of non-pilot KSA's, such as those pertaining to air traffic controller (ATC) and skilled computer gamers, could not be found. It is important to note that UAS applications, scenarios, and designs vary significantly, thus the skill-sets required on behalf of the pilots may be just as diverse.

Of secondary importance is how these highly automated systems interact with the pilot to provide for a seamless and coordinated control effort. It is especially important in the design of UAS that automation strategies be integrated in a way that allows for the pilot to remain actively involved and aware of the functions taking place within the system. The high-performance nature of the system requires an extensive amount of autonomy in order to operate, but a fully-autonomous system would leave out important human oversight and is deemed unsafe. Therefore, an appropriate level of automation is critical to the safety and performance characteristics of UAS design.

Currently, the U.S. Air Force and U.S. Navy calls for pilots with manned aircraft training, but this often results in a large amount of negative transfer effects when training them in a UAS environment (Pedersen, Cooke, Pringle, & Connor, 2006). The Human Systems Wing in the U.S. Air Force strongly recommends that, "Future work should focus on improving the empirical knowledge base on UAS human factors so evidence-based recommendations can be made when incorporating control migration in UAS design and operations (Thompson et al., 2006)." The FAA Civil Aerospace Medical Institute furthers this notion, by acknowledging that much research is needed to assess the KSAs for future UAS pilots (Williams, 2005). With the growing reliance on autonomy, and the diminishing accessibility of human intervention, a superior control interface design has never been more necessary in the realm of aviation (Hughes, 2008).

It is the intent of this current research to analyze the pilot's role in the UAS, and determine how the system best accommodates this role. Similar to manned aircraft, the pilot is directly responsible for insuring the overall safety of flight. For this reason, a human-centered approach will be assumed, rather than the mainstream technology-centered approach that is common in UAS research and design.

The layout of this thesis encompasses a broad literature review that should familiarize the reader with the intent of UAS operations. This will allow for a deeper understanding of what is expected on behalf of the UAS pilot, and the responsibilities that he/she must endure. Figure 1 outlines the structure of this thesis. To begin, a historical analysis will cover UAS development and its many real-world applications. This will be followed by a "system-of-systems" approach to UAS development and integration. There are many constraints and requirements that are imposed on UAS pilots and these will be discussed as well. The second half of the literature review will focus on the independent variables of main concern to this study: Experience (KSAs of Pilots and ATC) and Levels of Automation (Management by Consent and Management by Exception).

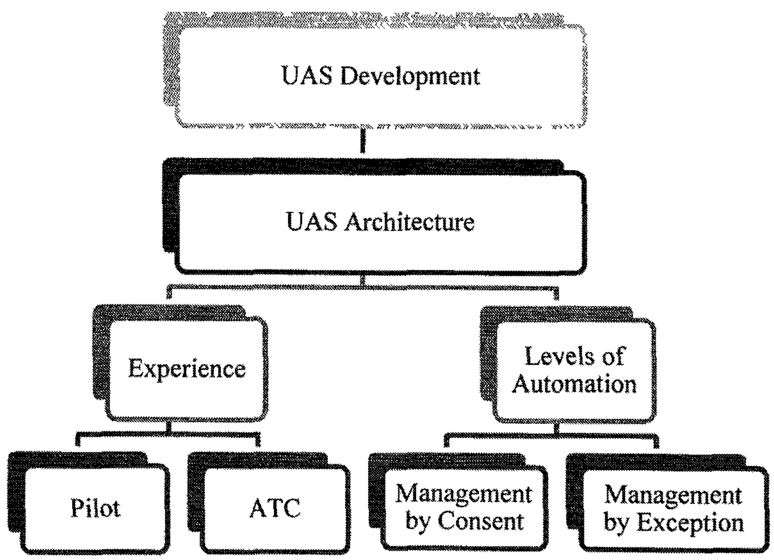

Figure 1. Thesis Layout

UAS: A Historical Analysis

Contrary to popular belief, initial concepts of these systems date back to the late 1800's by a highly notable scientist named Nikola Tesla (Newcome, 2004). In 1884, Tesla first conceptualized the design of a heavier-than-air unmanned aircraft flown by remote control using AC current. Tesla adamantly believed that his theory could be achievable through the use of radio frequencies and a ground-based controller, but the concept was readily dismissed as unachievable (Newcome, 2004). During the next 100 years, advancements in UASs occurred mainly as a result of wartime activities. Shortly after World War I, unmanned aircraft technologies really began to develop, following the advent of automatic stabilization, remote control, and autonomous navigation. Today, the military relies heavily on UASs to conduct missions that would otherwise be too boring, risky, or impractical for manned flight. These missions are often referred to as the "*Dull, Dirty, or Dangerous*" missions.

As the components of these systems became more advanced, and the missions more diverse, the terminology to describe these technologies has also evolved. UASs have undergone several name changes in their relatively short history. Depending on their intended use, they have been most commonly referred to as Remotely Piloted Vehicles, Unmanned Aerial Vehicles, and Remotely Operated Vehicles. The modern-day terminology, "Unmanned Aircraft Systems" was implemented to incorporate the entire system used to conduct the operation of these vehicles- inclusive of all the components required for operation (e.g. unmanned aircraft, CS, pilot, data-link, et al .) The timeline below depicts the chronology of names before it evolved into the term used today.

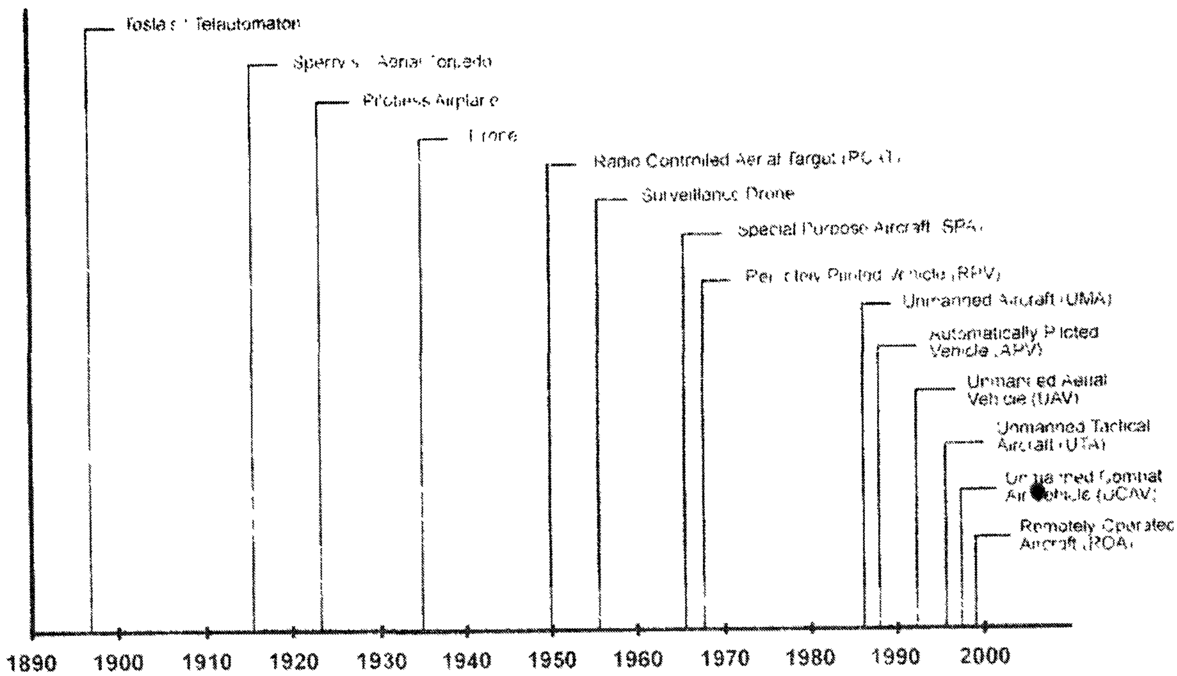

Figure 2. Chronology of names applied to robotic aircraft (Newcome, 2004)

Past UAS Operations

It is popular belief that the first unmanned aircraft was developed in 1916 and was called the Aerial Target. Some would even argue that primitive examples of unmanned aircraft were used in at least two wars prior to the development of the airplane, and date back to the year 1818. During this year, French scientist Charles Rozier developed the first recorded unmanned balloon designed to fire rockets on a target. The differences in historical findings are often due to how one defines a unmanned aircraft. Prior to the development of the airplane, balloons were used in place of an airplane, but unmanned balloons would not meet the criteria for many of the modern day definitions of UAS. Newcome (2004) provides us with a graphical depiction (see Figure 3) on how UASs evolved into what we had today. The roots denote the inventors that realized the feasibility of UAS operations, and the branches indicate the several classifications of unmanned aircraft that exist today. Note that only some of these unmanned aircraft classifications illustrated by the branches would fall under the classical UAS definitions provided by the FAA and DoD.

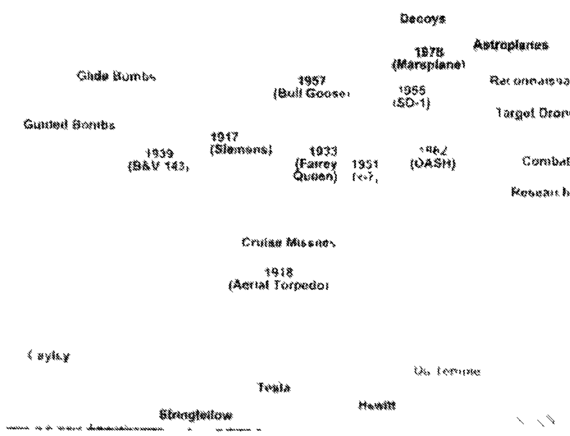

Figure 3. UAS Evolutionary Tree (Newcome, 2004)

Present UAS Operations

UASs have been around for approximately 100 years, but it hasn't been until recently that their capabilities have been recognized. The enormous growth of military interest towards UAS is a direct result of their proven performance and capabilities in the realm of surveillance, reconnaissance, and intelligence gathering, and more recently-attack missions (Hottman & Sortland, 2006). This highly sought after technology quickly grew in reputation after it was responsible for defeating the Iraqi Republican Guard several days sooner then what could have been achieved with manned aircraft. In 2005 alone, UASs had conducted over 100,000 flight hours in support of Operation Iraqi Freedom and Operation Enduring Freedom. By the end of 2008 that number increased to nearly 500,000 flight hours (excluding hand-launched systems) (Department of Defense, 2009).

Furthermore, UAS flight operations accomplished this effort without putting American pilots' lives in danger, due to the missions being flown by pilots residing within the U.S. borders (Scarborough, 2003; Guidry & Wills, 2004). The first combat deployment of a very modern UAS, known as the RQ-4 Global Hawk, consisted of a team of 86 members, 56 of which were contractors needed to conduct the flight portion of this new equipment (Guidry & Wills, 2004). A timeline of past, present, and future usage of several military UAS platforms are depicted in Figure 4.

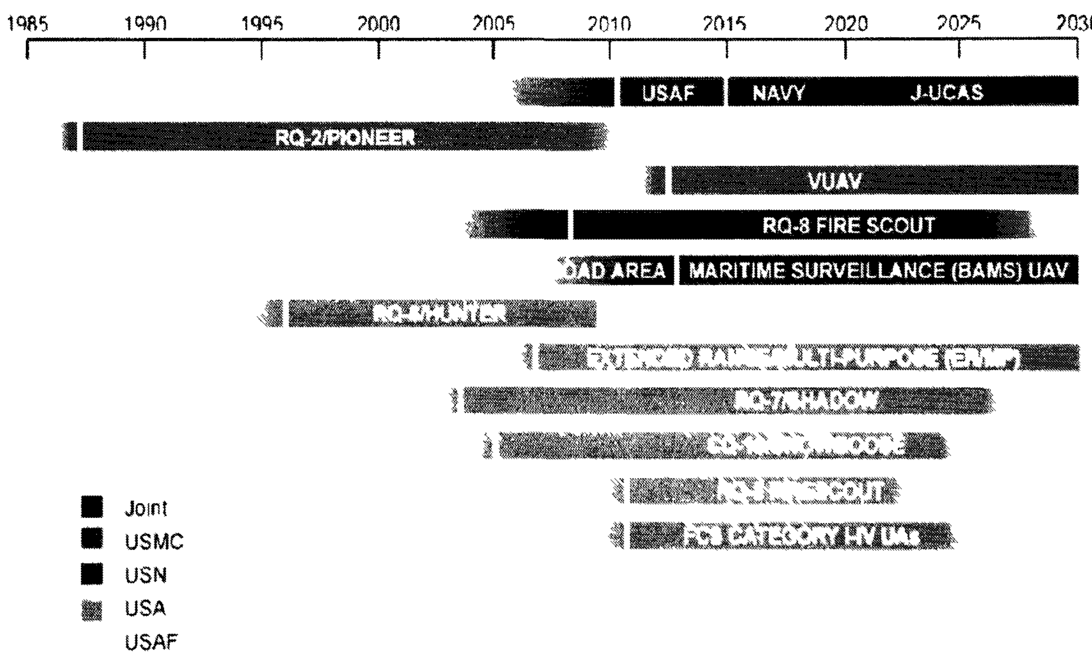

Figure 4. Timeline of DoD UASs (Department of Defense, 2005)

The tactical use of UASs surpassed the expectations of military commanders conducting wartime missions and the same is expected in civilian applications.

UAS Operational Diversity. The environment and intended mission scenarios in which UASs operate differ significantly. These technologies have advanced to the point where their application can be useful in many practical purposes such as drug interdiction, border monitoring, law enforcement, agriculture, communication relays, aerial photography and mapping, emergency management, and scientific and environmental research (Hottman, Gutman, & Witt, 2000; Nakagawa, Witt, & Hottman, 2001). These platforms would also operate in a number of environments, inclusive of those set up by regulating authorities. These vary by a multiple of factors, including airspace, weather conditions, and altitude. To suffice for each intended method of operation, user-interfaces would ultimately need to be designed in a fashion that allows for the most effective means of operation, thereby requiring different operating tasks on behalf of the pilot (Hottman & Sortland, 2006).

Methods of Control. The KSAs of UAS pilots would vary due to the wide range of operating platforms and user-interfaces that exist (Hottman & Sortland, 2006). Similar to manned flight, UASs have a wide range of uses, and the qualifications and certifications required for operation may differ depending on the intent of operation (O'hare & Roscoe, 1990). Some UASs are controlled from a hand-held device and remain in visual-line-of-sight (VLOS) where the pilot is controlling the aircraft within visual range. Highly automated methods of control require the pilot to establish waypoints, while automation is left to determine the appropriate aircraft settings to reach those destinations. On the other hand, some highly-autonomous UASs still require the pilot to operate the unmanned aircraft by manipulating the control surfaces from the control station (CS) in a similar fashion to fly-by-wire methods used in manned-flight.

Current UAS Pilots. Currently, there is no consistency in UAS pilot selection. The U.S. Air Force tends to select UAS pilot candidates that have received formal military flight training, but have recently graduated their first class of pilots trained specifically for UAS operation (Brinkerhoff, 2009). The Navy and Marine Corp select UAS pilots that already hold a private pilot license, while the Army selects UAS pilots who have never even flown a manned aircraft (McCarley & Wickens, 2004). Tirre (1998) noted that pilots transitioning from manned aircraft to UAS operations have faced boredom and difficulty maintaining situation awareness. It is also documented that transitioning pilots have difficulty switching flight environments due to the lack of vestibular and "seat-of-the-pants" sensory input obtained in manned flight. Weeks (2000) performed limited research in this area and concluded that there is a wide range of necessary qualifications that exist among UAS pilots, and more research is necessary to identify the KSAs of pilots that would best fit into UAS operations.

Future UAS Operations

The 2009 FAA NextGen Implementation Plan has cited that UAS is on the verge of taking flight in the NAS. Within the U.S., there are four different markets that may greatly benefit from UAS operations: military, civil government, research, and commercial applications. It is important to note that each market will have different constraints imposed on UAS operations. Examples of these constraints consist of several areas, inclusive of accessible technologies, regulations, public acceptance, cost-benefit, and other operational constraints (DeGarmo & Maroney, 2008). Regulatory controls, for example, may restrict commercial UAS operations entirely. The success of UAS in each market is dependent on the constraints imposed on their operation. Assuming that UAS capabilities are not heavily suppressed in each respective market, the chart below outlines predictions on when specific markets will be able to benefit from this aspiring technology.

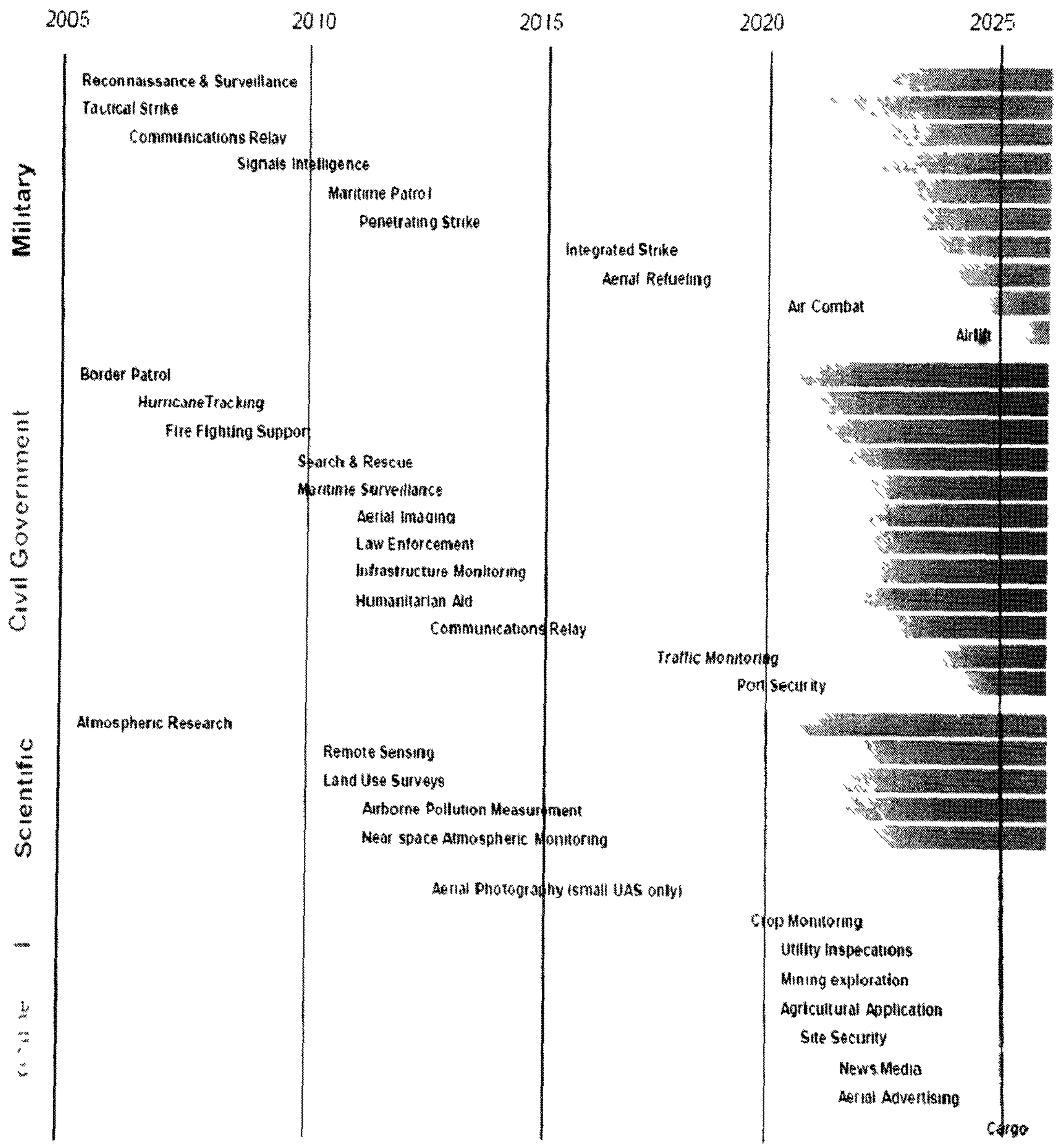

Figure 5. Current & Future UAS Potential Markets (DeGarmo & Maroney, 2008)

The potential operating scenarios are limitless, but have already been deemed useful in areas pertaining to agriculture, homeland security, telecommunications, and scientific research firms (McCarley & Wickens, 2005). The United Kingdom is anticipating the use of UASs for police and coastal patrol activities by the year 2012 (BAE Systems, 2007). In the same timeframe rapid spending and advanced technologies will enable the U.S. military to use UASs for a much broader range of missions inclusive of the Suppression of Enemy Air Defenses, Electronic Attack, and Deep Strike Interdiction (Department of Defense, 2005). Additionally, the Air Force Research Laboratory (AFRL) is actively researching the capabilities of Small Unmanned Aerial Vehicles (SAVs) and Micro Aerial Vehicles (MAVs) to perform target detection and identification missions within urban environments (Hughes, 2008). An aerospace and defense consulting agency has predicted that the U.S. will spend nearly $55 billion over the next decade towards the Research, Development, Testing, and Evaluation (RDT&E) efforts of UAS technologies. These research efforts will be comprised of the most dynamic growth sectors of the worlds' aerospace industry (Teal Group, 2009). It is no longer a question as to *if* unmanned systems will become a part of our everyday lives, but more of a question as to *when*. The technology is feasible; it's now a matter of determining the most safe and effective route to guide its success. Among the means of achieving compliance to operate within our current NAS framework, there lies a fundamental question as to how the aircraft should be controlled and who should do so. The selection of well-suited pilots linked to adequate designs of UAS control stations is paramount to the safe integration of these cutting edge systems.

The wide-range of potential for UAS operations is already foreseen, but how these operations are conducted is left to future research. It is currently required that humans remain active in UAS operations. This is necessary for a variety of reasons, including re-tasking the mission, communicating with other aircraft and ATC, and to file flight plans. The reasons may vary from system to system, but determining who will pilot the UAS is one of the biggest issues in future UAS development (Pederson et al., 2006).

Unmanned Aircraft Systems Architecture

A system ultimately behaves in the way in which it was designed, rather than how it was expected or intended. This is critical to the system design where the operations take place in a complex, ever-changing operating environment (Williams, 2008). Systems are designed based on an understanding of the structure, function, and dynamics of the intended operating environment, as well as any foreseen variability that takes place within that environment. Since automated systems are literal minded agents, any inaccuracies, misconceptions, or simplifications in the design will inevitably lead to undesirable results (Hughes, 2008; Batkiewicz et al., 2006). For this reason it is imperative that the users remain a central focus in the design process, especially regarding situations where the pilot must recognize and mitigate unintended automation complications before they result in a catastrophe.

Equivalent Level of Safety (ELOS)

UAS operations must meet or exceed an "equivalent level of safety" (ELOS) as its manned counterpart (FAA Order 7610.4k, 2004). Currently, a military review indicated that UAS mishaps are nearly double the magnitude of manned-aircraft (Williams, 2004). Up to 69% of these occurrences are due to human factors related issues, often resulting from poor human systems integration. A thorough review of these mishaps suggested that attention factors were of primary cause. (Tvaryanas, Thompson, & Constable, 2006). The Air Force Scientific Advisory Board (AFSAB) blames pilot inadequacies on the human/system interface design as a limiting factor in UAS safety and control (Worch, Borky, Gabriel, Heiser, Swalm, & Wong, 1996). A major challenge is to discover a human interface design that adequately keeps the pilot actively involved and fully aware of the flight operations taking place (Walter, Knutzon, Sannier, Oliver, 2004).

A Regulatory Assessment

The current national airspace system is comprised of an enormous multitude of regulations, procedures, and operational requirements that the pilot must adhere to. This framework enables the ability of safe operation among the people that share the NAS, and also protects lives and property on the ground. The Federal Aviation Administration (FAA) has recognized the importance of UAS technology and is adamantly concerned with its safe implementation, especially on behalf of the pilot's new role. As a result, the FAA is faced with an unprecedented dilemma: the massive architecture of governance was built around the assumption that the human operator would reside inside of the aircraft; with the onset of UAS technologies, this is no longer the case. As the human operator gets removed from the aircraft, there are numerous complications that arise and the FAA is seeking ways to deal with these issues. Fulfilling the following Federal Aviation Regulations (FARs) are deemed to be largest barriers in the transition from manned to unmanned flight:

- **19 CFR 91.3 (a) Responsibility and authority of the pilot in command**
  The pilot in command of an aircraft is directly responsible for, and is the final authority as to, the operation of that aircraft.
- **19 CFR 91.111 (a) Operating near other aircraft**
  No person may operate an aircraft so close to another aircraft as to create a collision hazard.
- **19 CFR 91.113 (b) Right-of-way rules: Except water operations**
  When weather conditions permit, regardless of whether an operation is conducted under instrument flight rules or visual flight rules, vigilance shall be maintained by each person operating an aircraft so as to see and avoid other aircraft. When a rule of this section gives another aircraft the right-of-way, the

> pilot shall give way to that aircraft and may not pass over, under, or ahead of it unless well clear.
>
> (Reynolds 2008; Hottman, Hanson, & Berry, 2008)

UAS operations will need to conform to the rules, regulations, standards and expectations of the future NAS (DeGarmo & Maroney, 2008). In meeting this objective, Hottman and Sortland (2006) highlight the importance of establishing a system that caters to the pilot whom insures that these ELOS objectives are met, even during unintended circumstances. The pilot must be able to create an accurate assessment of the flight situation, without being overworked. The user-interface, inclusive of the automation strategies, plays an important role to insure that this happens.

There are a number of research efforts underway to address the regulatory challenges associated with the integration of UAS into the NAS. Well-respected regulating authorities such as the Radio Technical Commission for Aeronautics (RTCA), the American Society for Testing and Materials (ASTM), Society of Automotive Engineers (SAE), National Aeronautics and Space Administration's (NASA) Access 5, and the European Organisation for Civil Aviation Equipment (EROCAE) have all participated in defining recommendations for the minimum requirements of UAS components and operations (DeGarmo & Maroney, 2008; Tvaryanas et al., 2006). As these standards, regulations, and constraints for UAS operations are being developed, regulating bodies are limited by the lack of research focusing on the most critical part of the system - the human component (Tvaryanas et al., 2006).

A Technological Assessment

To date, there are no FAA-certified UASs operating in the NAS. Research is currently being conducted to develop adequate systems, but there seems to be a stand-off between the FAA and the industry. "The FAA wants technology answers before writing new regulations; operators and manufacturers want to know the regulatory landscape before committing to major new investments in technology" (Wilson, 2007). Developing a system that is capable of performing equivalent to that of a human is no small feat.

Currently, Certificates of Authorizations (COA) and/or experimental certificates can be obtained by public (state-owned/operated) and civil (typically industrial and manufacturers) entities on a case-by-case basis when special provisions are met (AIR-160, 2008). Commercial operations are strictly prohibited, and it may be years before they are granted access to operating within the NAS (DeGarmo & Maroney, 2008).These certificates are essentially waivers that allow for an approved UAS to operate within the NAS under special restrictions and accommodations. To date, a very limited number of COAs have been granted to UASs. These allow for new technologies to be tested, but certain provisions must be made to accommodate for undeveloped technologies.

Perhaps the biggest technological barrier for commercial UAS operations is the ability to replace the "see-and-avoid" (SAA) tasks that are required by pilots of manned aircraft. There have been exceptional improvements on detect, sense, and avoid (DSA) systems, but none have been certified for use. It is understood that this type of system must be highly autonomous (very little human involvement) to fully autonomous (i.e. in case of communication failure). To date, only portions of an adequate sense-and-avoid system exist, and much of it is economically impractical, along with size, weight, and power (SWAP) restrictions (Wilson, 2007).

Hunn (2006) suggests that user interface displays have the potential to enhance the pilot's ability to gather system information and become compatible with the system.

Innovative information cues and presentation options may help UAS pilots compensate for certain "missing" information and maintain a degree of situational awareness equivalent to or better than that of manned flight (SC-203, 2007; Pederson et al., 2006). Therefore, it may be a more practical approach to evaluate the combination of the pilot/user-interface compatibility, rather than evaluating the performance characteristics of each entity on a separate basis.

A Human Factors Assessment

Wiener and Curry (1980) pioneered the term "clumsy automation" when they discovered adverse effects that had occurred due to the implementation of automation. In some cases, operator workload was exacerbated in response to automation; meaning workload was increased in times of already high workload, but decreased in times of already low workload (Metzger & Parasuraman, 2005). An example of this is when the auto-pilot feature on an aircraft reduces the workload on pilots during cruise flight where workload is typically low, but increases the workload on pilots during the landing portion of flight where workload is typically high. These findings, in conjunction with an abundance of faulty automation applications, were an initial step in the discovery of several automation-induced problems.

It is highly agreed upon that automation has the potential to substantially change the way that humans perceive the situation and provide feedback in ways that were never intended by the system designers. (Bainbridge, 1983; Billings, 1997; Parasuraman & Riley, 1997; Sarter & Amalberti, 2000; Wiener & Curry, 1980). The complexity of automated systems have also raised concerns on operator workload, monitoring skills, proficiency, target detection, complex decision making, and situation awareness degradation (Endsley, 1996; Parasuraman, Molloy, & Singh, 1993; Wiener, 1988; Wiener & Curry, 1980; Galster, Bolia, Roe, & Parasuraman, 2001; Rovira, McGarry, & Parasuraman, 2002; Wickens & Hollands, 2000). This will ultimately alter human vigilance decrements, detection capabilities, limited system flexibility, and automation biases (Parasuraman, Sheridan, & Wickens, 2000). Additionally, automated systems induce an effect known as automation-induced complacency, where the operator becomes out-of-touch with the system operation, resulting in degraded performance (Farrell & Lewandowsky, 2000; Parasuraman & Byrne, 2003; Parasuraman et al., 1993). These automation-induced complications are of high concern in the realm of UAS where the flying platform is said to be partially to fully- autonomous, in addition to the pilot being physically separated from the aircraft. Not only does this pose many safety concerns, it also limits the human pilot's ability to work as a fail-safe.

McCarley and Wickens (2004) analyzed a primary consequence that occurs by separating the pilot from the aircraft. Rather than directly obtaining sensory input from the surrounding environment, pilots are limited by the amount of information portrayed to them by the user-interface. This information ranges from ambient visual information to vestibular input and sound. The result of being restricted from this sensory input is termed "sensory isolation". Similarly, there is also a problem referred to as out-of-the-loop unfamiliarity (OOTLUF) (Wickens, 1992). Humans typically construct a poor mental model of the situation and develop insufficient SA when they are not actively involved in the system operations (Endsley, 1996; Endsley & Kiris, 1995). A "mental model" is deemed as the ability to create an accurate mental representation of something, such as a remote operating environment, based on one's own past experiences (Moray, 1997). Furthermore, laboratory findings have suggested that humans are poor monitors over systems, and do not play a good role as a fail-safe in highly automated systems (Parasuraman et al., 1993; Pope & Bogart, 1992). Early UAS designs reinforced this notion after they realized that pilots lacked adequate SA and did not have the capacity to override automated functions when necessary (Department of Defense, 2003). Studies performed on USAF and Army pilots indicated high levels of boredom, degraded target detection, decreased recognition performance, and increased reaction times (Thompson et al., 2006; Barnes & Matz, 1998). Conclusively, if the user-interface does not adequately coincide with the human operator, and vice-versa, than the overall system performance is degraded (Lorenz, Di Nocera, Rottger, & Parasuraman 2002).

In order for the pilot to make timely and effective decisions, he/she must be able to gain an accurate assessment of the unmanned aircraft in its operating environment. In order for this to exist, the machine and human should interact dynamically as a single system (Putzer & Onken, 2001). Furthermore, Schulte (2002) argues that the operator should also have static background knowledge relevant to the application domain, as well as dynamic solution knowledge generated as an output of the cognitive sub-processes. The resulting decision made by the operator will be based on their prior knowledge applied to the interpretation of the information forwarded by the user interface.

The increasing reliance on automation in the realm of aviation results in an increase in challenges to design safe, reliable, and effective automated systems. It is all too common for functions that were traditionally performed by a human entity to be replaced by fickle automated systems that have failed in highly dynamic and often unpredictable environments. In an attempt to transcend from historic mistakes in automation, research has indicated that a more favorable approach is to develop systems that allow for better coordination between human and automation to allow for adequate human oversight (Hughes, 2008). The pilot in command (PIC) assumes sole responsibility for the operation of the UAS, and is a fundamental part of the system, but how the user-interface compliments his/her function will ultimately determine the success of UAS.

UAS Pilot Selection

The selection of UAS pilots is one area that remains to be investigated (Nelson & Bolia, 2006). Several military branches are selecting experienced pilots to perform these duties, but many wonder if this is the correct approach. Hottman & Sortland (2006) suggest that the KSAs of UAS pilot candidates need to be determined empirically. They also suggest that the KSAs required for UAS pilots not only differ significantly from manned flight, but also between the various UASs, taking into account the level of automation that is necessary to fly the unmanned aircraft.

Tirre (1998) acknowledges that research for UAS pilots should address the following areas of concern: 1) the selection and training of UAS pilots to accommodate the necessary situation awareness tasks, and 2) the effects of UAS automation on potential pilots. Situation awareness is especially critical, and can be improved by particular interfaces but individual differences among pilots with varying KSAs still remains an important issue (Gawron, 1997).

Pilot Skill Sets

Pilots of manned-aircraft perform their job function from an egocentric standpoint. In other words, they reside within the operating environment. Due to their location of operation, pilots are generally able to obtain sensory information directly from the surrounding area. This is inclusive of sounds and kinesthetic clues that help determine flight characteristics such as airspeed, flight attitude, and power settings. An important aspect of manned flight is the ability to use vision as a primary means of obtaining situation awareness and performing collision avoidance functions. Direct human sensing is a key element found in manned-flight and is an important function in safely achieving the desired objective of safe flight (SC-203, 2007). Consequently, the slogan "flying by the seat of your pants" refers to a pilot's ability to perform flight functions primarily on the sensory cues obtained from the surrounding environment. When a sensory cue changes unexpectedly, an alert pilot will further assess the situation and take preventive measures to mitigate risk.

A common phrase used in the aviation community typically sums up the duties of a pilot: *"Aviate, Navigate, Communicate"* (Machado, n.d.). *Aviate* refers to the responsibility of controlling the airplane safely using the controls available (i.e. flight instruments, flight controls, etc.). *Navigate* refers to the obligation of monitoring where the aircraft is located and determining how to get it to where it needs to be. *Communicate* refers to the task of keeping other pilots and ATC informed of the status. For obvious reasons, *aviate* remains the top priority for the pilot, followed by *navigate*, and then *communicate*. (Note: In a highly automated UAS setting, these pilot functions tend to be in reverse order, as automation accommodates much of the *aviate* and *navigate* roles.)

Air Traffic Control Skill Sets

Air Traffic Controllers (ATC) performs their job function from an exocentric standpoint. This means that they manage airspace operations outside the range of their immediate senses (Hunn, 2005). They monitor the airspace to safely conduct the flow of traffic and prevent collisions and hazardous situations. The job function requires that they quickly assess the situation by absorbing the data given to them through radar displays and communicating with pilots. They control several aircraft at once while visualizing the position of each aircraft, in time and space, in order to develop strategic decisions regarding heading, airspeed, and altitude.

An in-depth KSA profile has been developed in an effort to determine ability requirements for air traffic controllers (EiBfeldt, & Heintz, 2002). The main categories are divided up into five segments: cognitive abilities, psychomotor abilities, sensory abilities, interactive/social abilities, knowledge/skills. Multiple abilities are evaluated under each category, totaling 81 different abilities in all. The core cognitive abilities of controllers are 'Time Sharing', 'Selective Attention', 'Visualization', and 'Speed of Closure'. These allow the controller to quickly and routinely organize different pieces of information into a meaningful pattern, while also having the ability to shift between tasks as appropriate. The top abilities in the psychomotor category are 'Control Precision', 'Response Orientation', 'Rate Control', and 'Reaction Time'. These all relate to the speed and coordination required to operate the necessary control and communications equipment. The top abilities in the sensory category are 'Near Vision', 'Hearing Sensitivity', 'Auditory Attention', 'Speech Recognition', and 'Speech Clarity'. These abilities are necessary to monitor the radar control equipment while communicating with other controllers or pilots. Under the knowledge category, 'Map Reading', and 'Spelling' are seen as important factors in conducting job duties.

It is important to note that the required abilities differ among various ATC positions and systems being used. Newer systems tend to require significant increases in abilities related to computer usage (EiBfeldt, & Heintz, 2002).

UAS Pilot in Command

There is little resistance to implement the pilot into the unmanned aircraft system architecture, but there still remains a high level of speculation and debate as to the role the pilot should perform and how the technology should support their mission (Hughes, 2008). The selection of these pilots will remain an important aspect of maintaining a highly dynamic system design. The range in performance characteristics of unmanned aircraft is vast, and the skill-set required for UAS pilot recruitment may be equally varied.

A UAS pilot will and always will be a necessary component of the system (Pederson et al., 2006), however, the required KSAs that an unmanned aircraft pilot should posses have yet to be determined (Pederson et al., 2006). Increases in UAS automation is decreasing the necessity for traditional pilot skills (DeGarmo & Maroney, 2008), and instead requiring a heightened need for monitoring and collaborative decision making skills. An alternative approach is to consider the expertise of an air traffic controller, especially due to the similarity of multitasking and familiarity of exocentrically controlling a variety of air vehicles differing in space and timing (Hunn, 2005).

Schulte (2002) suggests that the reason for many of the negative impacts created by automation can be due to inconsistencies between the automated machine functions and how the pilot perceives them (Schulte, 2002). This reasoning implies that there will be differences in system perception and operation, based on an individual's background; hence the differences in formal training among pilots and air traffic controllers having an impact on their perception and decision making ability. Likewise, the overall system design must be able to work in concert with the operator in which it is paired with. The superior design of the overall system, inclusive of the operator, is directly correlated to the pinnacle of its success.

Automation

Automation is a very complex and highly debatable topic in the research and engineering fields. Sheridan (2002) defines automation as "(a) the mechanization and integration of sensing the environmental variables (by artificial sensors); (b) data processing and decision making (by computers); and (c) mechanical action (by motors and devices that apply forces on the environment) or information action' by communication of processed information to people". More simply, Parasuraman and Riley (1997) define automation as "the execution by a machine agent (e.g. computer) of a function previously carried out by a human operator." Automation by design only does what it has been *told* to do, rather than what is expected, intended, or desired (Hughes, 2008). It is for this reason that a human-operator, who inhibits the ability to foresee the unexpected and take corrective action to mitigate unintended situations, is an essential part of the system design. In an ever-changing aerospace environment, the automated part of the system is more vulnerable to unforeseen situations.

With an ideally designed automated system, there has shown to be improvements to the operators SA, cognitive ability, and perceptual grounds for decision-making (Wiener, 1988). Studies specific to UAS have even suggested that there is a reduction of operator workload with increased automation (Dixon, Wickens, & Chang, 2003). Automated systems have also played a significant role in improving the perceptual and cognitive abilities of the flight crew, while providing comfort to passengers, as well as increasing fuel efficiency and reducing flight times (Wiener, 1988).

There are several applications that are currently being used in the modern-day NAS that assist the pilot with tasks that were once difficult and perhaps infeasible. Automated technologies used throughout the aviation arena range from Flight Management Systems (FMS) to Automatic Dependent, Surveillance-Broadcast (ADS-B) systems. Automation assists the pilot in number of tasks including the detection of other flight traffic, engine and fuel monitoring, and even flying the airplane. In fact, automated technologies allow some modern jet aircraft ranging from the Boeing 747 to the F-117 Stealth Fighter to complete an entire flight with very little pilot interaction.

The automated machine offers several advantages over a human operator, but the operator also has advantages over the machine. For instance, machines can carry out complex calculation quickly and precisely. Unlike humans, automated machinery rarely falters, and does not become tired, distracted, or bored. Humans on the other hand, are capable of planning, overseeing, and making intelligent decisions in time of uncertainty or automation failure. If they work together effectively, then they can achieve superior goals greater than the sum of the individual parts. However, this is not always the case. Hughes (2008) warns us that automation is not a panacea under conditions of uncertain changing situations. History has indicated that automated systems fail to perform as they were intended. He furthers this notion by identify three points that are inherent to systems:

- All cognitive systems are finite (people, machines, or combinations)
- All finite cognitive systems in uncertain changing situation are fallible.
- Therefore, machine cognitive systems (and joint systems across people and machines) are fallible

(Hughes, 2008)

It is clear that systems are inevitably fallible, especially in the highly dynamic and often unpredictable environments that UASs plan to operate within. Even if the probability of system fallibility is low, the magnitude of an adverse consequence often remains high. This is why it is so critical to design a system that allows for a pilot with the right skill-sets to be actively involved in the system operation.

Human-Centered Automation

Unlike conventional automation techniques, human-centered automation focuses on distributing tasks among the human and machine so that a team effort is achieved (Endsley, 1996; Billings, 1997). Human-centered automation is a technique that allows the human to function effectively as part of system, rather than simply an add-on to an already existing system. Information gathered and forwarded by the automated system is critical to the pilot's ability to quickly and accurately assess the situation that the unmanned aircraft is encountering. A poorly designed system can leave the pilot with only bits and pieces of information, which can result in poor SA and cognitive under-load, thereby resulting in overall poor performance (Sanders & McCormick, 1993). Therefore, humans must know how to operate the automated system, and the system must be designed in a way that reinforces an actively informed pilot. For this to happen the human operator must be fed correct information in the right amount of time and in the right manner. In the case of UAS operations, there is little room for error or inaccuracies to take place. C.E. Billings (1997) identifies several key principles that make up human-centered automation in a modern aviation context. They are as follows:

Premises:
- The pilot bears the responsibility for safety of flight.
- Controllers bear the responsibility for traffic separation and safe traffic flow.

Axioms:
- Pilots must remain in command of their flight.
- Controllers must remain in command of air traffic.

Corollaries:
- The pilots and controller must be actively involved.
- Both human operators must be adequately informed.
- The operators must be able to monitor the automation assisting them.
- The automated systems must therefore be predictable.
- The automated systems must also monitor the human operator.
- Every intelligent system element must know the intent of other intelligent system elements.

(Billings, 1997)

The benefits of automation are ultimately contingent on how automation strategies are applied and distributed among the machine and the pilot. Appropriate allocation of system functions is essential to overall system performance.

Function Allocation

Sheridan (1998) defined function allocation as "the assignment of required functions (tasks) to resources, instruments, or agents (either people or machines)". For years, human factors experts have been trying to identify ways in which to best distribute tasks between human and machines. Hughes (2008) argues that designers should develop systems that provide for effective coordination between the user and the machine, rather than separate tasks between the two. This is effectively known as "team play". Richard Pew (1998) relates this concept to that of a symphony, whereby the composer aims at acquiring a harmonious sound by assigning individual instrument parts that work in concert with each other. Likewise, certain tasks should be appropriately divided up between the human and the machine in a way that will safely and effectively achieve the overall objectives.

The process of applying automation can be a difficult task in discerning which functions should be automated and what functions should be left up to the human. Schulte (2002) provided us with a high-level example of the strengths of humans and that of machines, as well as how they collaborate:

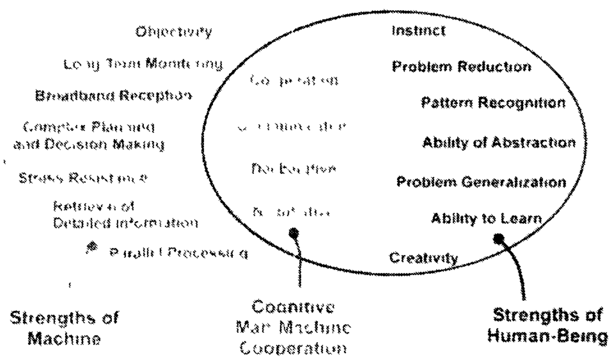

Figure 6. Synergetic resources for man-machine cooperation (Schulte 2002)

Sanders & McCormick (1993) point out that humans are typically better at sensing unusual situations in the environment, deriving alternative solutions, and the detection of unexpected stimuli. Whereas machines are excellent at conducting pre-specified tasks, endure extreme environmental elements, and reliably repeat their pre-assigned functions. It should be noted that along with the inevitable progression of technology, the capabilities of machine will also evolve, resulting in the possibility of current human strengths being overcome by that of a machine.

Many conventional systems do not provide for an adequate level of human involvement within the system operation, thereby placing the entire system at a much higher risk for failure. It is also common for system designers to only focus on decreasing workload but this often results in a decrease in situation awareness, thereby increasing risk for failure. Due in large part to this concept, a U.S. Air Force Scientific Advisory Board concluded that the allocation of functions, and human-machine interface designs are both major shortfalls in UAS operations (Worch, 1996). An ideal system should be designed in a way that decreases workload, while increasing SA. Since one is often gained at the sacrifice of another, both should be measured in unison to discover the best desired combination of the two.

Studies of Automation on Workload

Workload is a general term used to describe the cost of accomplishing task requirements for the human element of a man-machine system (Hart & Wickens, 1990). Essentially, this comes down to a supply-and-demand type of concept. As a task becomes more demanding, the human must expend a higher amount of workload to compensate. Although humans are typically agile creatures by nature, there comes a point where demands exceed the amount of workload available, resulting in diminished performance (Sarno & Wickens, 1995). It is suggested that workload can be measured by numerous factors including: physical demand, mental demand, time pressure, effort expended, performance level achieved, frustration experienced, and annoyance experienced (Spirkovska, 2006).

Performance can be degraded as a result of both high and low levels of workload demands (Crescenzio, Miranda, Periani, Bombardi, 2007). Low levels of automation typically demand higher levels of operator workload, whereas high levels of automation demand lower levels of operator workload but inevitably result in decreased SA, or out-of-the-loop performance decrements. Out-of-the-loop performance decrements require the operator to expend an abundant amount of workload in a short amount of time to regain in-the-loop familiarity with the situation. Crescenzio suggests that an ideal human-centered interface should provide the human with the following:

- Low level of operator workload: the operator would have to spend few resources in terms of time and cognitive effort to command the vehicle, in order to manage the mission and analyses the information coming from onboard system.
- High level of operator situation awareness: the operator should be provided with a comprehensive view of the overall mission scenario, in order to understand the mission state and detailed vehicle state during the mission, enabling him to score and order all the information to develop the optimal command sequence

(Crescenzio et al., 2007)

It is noteworthy to mention that just as supply and demand continually fluctuate in the real business market, so does that of workload and SA. Therefore, it can be suggested that there will be a point of equilibrium where workload supply and SA demands will result in best achievable performance; yet fluctuations can be expected through time due to constant changes in factors such as operator characteristics and environmental concerns.

Alleviating pilot workload, while maintaining (or increasing) adequate SA should be of primary importance in the design of a UAS. A disengaged pilot often results in out-of-the-control-loop performance decrements, deficits in SA, sporadic workload, and inability to regain system control (Kaber & Endsley, 1997).

Studies of Automation on Situation Awareness

Endsley (1988) formally defines SA 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 future." Endsley (1995) later classifies SA into three levels to better apply towards complex systems. Level 1 requires the pilot to perceive relevant environmental information (e.g. the presence of another aircraft). Level 2 requires the pilot to comprehend the lower level situation to predict how it will affect the current situation (e.g. the aircraft is in conflict with current flight path). Level 3 requires the pilot comprehends the lower levels to predict future outcomes (e.g. a collision with the aircraft will occur unless a heading adjustment is made).

In the event that systems are highly automated, achieving a state of Level 3 SA is very difficult to accomplish. Even achieving Level 2 SA has shown to be problematic (Carmody & Gluckman, 1993; Endsley & Kiris, 1995). Endsley (1997) summarizes these problems as:

- Vigilance decrements associated with monitoring, complacency due to over–reliance on automation, or a lack of trust in automation can all significantly reduce SA as people may neglect monitoring tasks, attempt to monitor but do so poorly, or be aware of indicated problems, but neglect them due to high false alarm rates.
- Passive processing of information under automation (as opposed to active manual processing) can make the dynamic update and integration of system information more difficult.
- Changes in form or a complete loss of feedback frequently occur either intentionally or inadvertently with many automated systems.
- Failure to achieve desired reductions in operator workload as monitoring is a demanding task and the automation itself introduces new kinds of workload

(Endsley, 1997)

An ideal method of designing a system that allows for a cooperative human-system synergy is accomplished by strategically determining the appropriate level of automation (LOA) that minimizes the impacts of SA. "LOA represents a strategy for improving the functioning of the overall human-machine system by integrating the human and automated system in a way that allows the human to function effectively as part of the system (Endsley, 1997)."

Levels of Automation

Levels of automation is defined as "the level of task planning and performance interaction maintained between the human operator and computer in controlling a complex system (Kaber & Endsley, 2003)." The level in which the machine and/or human are involved in the particular function is deemed to be the level of automation that is implemented into the design.

Endsley & Kaber (1999) point out that automation is not an all or nothing concept. Instead, it can be applied to a multitude of tasks in various ways. Sheridan and Verplank (1978) discovered this concept early on while establishing automation techniques for teleoperated undersea vessels. The objective was not to assign individual tasks between the human and the machine, but to establish a 'game-plan' for a variety of tasks in a way that kept both assets actively involved. This coordination technique kept the human in the loop, while allowing for 'team-play' to be carried out. Table 1 lists the various levels of automation that could be associated with each task.

Table 1

Sheridan & Verplank's Level of Automation. (Sheridan & Verplank, 1978)

(1) Human does the whole job up to the point of turning it over to the computer to implement
(2) Computer helps by determining the options
(3) Computer helps to determine options and suggests one, which human need not follow
(4) Computer selects action and human may or may not do it
(5) Computer selects action and implements it if human approves
(6) Computer selects action, informs human in plenty of time to stop it
(7) Computer does whole job and necessarily tells human what it did
(8) Computer does whole job and tells human what it did only if human explicitly asks
(9) Computer does whole job and decides what the human should be told
(10) Computer does the whole job if it decides it should be done and, if so, tells human, if it decides that the human should be told.

Nearly ten years later, Endsley (1987) developed a similar model that focused on the human component of the system, rather than the machine. Endsley also added levels that would accommodate for fully-autonomous and fully-manual system functions. Table

2 provides a conceptual framework as to the level in which the human is involved in the task.

Table 2

Endsley's Level of Automation. (Endsley, 1987)

(1) **Manual Control**- no assistance from system
(2) **Decision Support**- by the operator with input in the form of recommendations provided by the system
(3) **Consensual Artificial Intelligence**- by the system with the consent of the operator required to carry out actions
(4) **Monitored Artificial Intelligence**- by the system to be automatically implanted unless vetoed by the operator
(5) **Full Automation**- no operator interaction

Endsley and Kaber (1997, 1999) further expanded this concept to include a wider range of cognitive and psychomotor skills necessary to complete tasks in cooperation with a machine counterpart. The applicability of the updated concept applies to many various domains that shared a variety of commonalities including: "(1) multiple competing goals, (2) multiple tasks competing for an operator's attention, each with difference goals, (3) high task demands under limited time resources (Kaber & Endsley, 2003)." Likewise, there were also four intrinsic functions or 'roles' discovered for each level of automation:

1. Monitoring- which includes taking in all information relevant to perceiving system status (e.g. scanning visual displays)
2. Generating-formulating options or task strategies for achieving goals;
3. Selecting-deciding on a particular option or strategy
4. Implementing-carrying out the chosen option through control actions at an interface

(Kaber & Endsley, 2003)

Ensley's level of automation taxonomy is displayed in Table 3. A detailed explanation of each LOA is defined in Figure 8.

Table 3

Endsley's LOA Taxonomy. (Kaber & Endsley, 2003)

Level of Automation	Roles			
	Monitoring	**Generating**	**Selecting**	**Implementing**
(1) Manual Control	Human	Human	Human	Human
(2) Action Support	Human/Computer	Human	Human	Human/Computer
(3) Batch Processing	Human/Computer	Human	Human	Computer
(4) Shared Control	Human/Computer	Human/Computer	Human	Human/Computer
(5) Decision Support	Human/Computer	Human/Computer	Human	Computer
(6) Blended Decision making	Human/Computer	Human/Computer	Human/Computer	Computer
(7) Rigid System	Human/Computer	Computer	Human	Computer
(8) Automated Decision Making	Human/Computer	Human/Computer	Computer	Computer
(9) Supervisory Control	Human/Computer	Computer	Computer	Computer
(10) Full Automation	Computer	Computer	Computer	Computer

(1) Manual— The human performs all tasks including monitoring the state of the system, generating performance options, selecting the option to perform (decision making) and physically implementing it.
(2) Action support— At this level, the system assists the operator with performance of the selected action, although some human control actions are required. A teleoperation system involving manipulator slaving based on human master input is a common example.
(3) Batch processing— Although the human generates and selects the options to be performed, they then are turned over to the system to be carried out automatically. The automation is, therefore, primarily in terms of physical implementation of tasks. Many systems, which operate at this fairly low level of automation, exist, such as batch processing systems in manufacturing operations or cruise control on a car.
(4) Shared control— Both the human and the computer generate possible decision options. The human still retains full control over the selection of which option to implement, however, carrying out the actions is shared between the human and the system.
(5) Decision support— The computer generates a list of decision options, which the human can select from, or the operator may generate his or her own options. Once the human has selected an option, it is turned over to the computer to implement. This level is representative of many expert systems or decision support systems that provide option guidance, which the human operator may use or ignore in performing a task. This level is indicative of a decision support system that is capable of also carrying out tasks, while the previous level (shared control) is indicative of one that is not.
6) Blended decision making— At this level, the computer generates a list of decision options, which it selects from and carries out if the human consents. The human may approve of the computer's selected option or select one from among those generated by the computer or the operator. The computer will then carry out the selected action. This level represents a high-level decision support system that is capable of selecting among alternatives as well as implementing the selected option.
(7) Rigid system— This level is representative of a system that presents only a limited set of actions to the operator. The operator's role is to select from among this set. He or she cannot generate any other options. This system is, therefore, fairly rigid in allowing the operator little discretion over options. It will fully implement the selected actions, however.

(8) Automated decision making— At this level, the system selects the best option to implement and carries out that action, based upon a list of alternatives it generates (augmented by alternatives suggested by the human operator). This system, therefore, automates decision making in addition to the generation of options (as with decision support systems).
(9) Supervisory control— At this level, the system generates options, selects the option to implement and carries out that action. The human mainly monitors the system and intervenes if necessary. Intervention places the human in the role of making a different option selection (from those generated by the computer or one generated by the operator); thus, effectively shifting to the Decision Support LOA. This level is representative of a typical supervisory control system in which human monitoring and intervention, when needed, is expected in conjunction with a highly automated system.
(10) Full automation— At this level, the system carries out all actions. The human is completely out of the control loop and cannot intervene. This level is representative of a fully automated system where human processing is not deemed necessary.

Figure 7. LOA Taxonomy Definitions (Kaber & Endsley, 2003)

Billings (1997), offers a similar approach to automation styles directly related to pilot and ATC operations. Among those are two levels of automation that are approached prior to reaching a fully autonomous state of operation: management by consent and management by exception.

Management by Consent

MBC is a management style that incorporates lower levels of automation. This management style allows the machine to perform functions only when given permission by the operator, and correlates with levels 6 and 7 of Kaber & Endsley's (2003) level of automation taxonomies. This style of automation associates the pilot as a team player in the system functions, since he/she must designate the tasks to be conducted by automation. This often results in higher SA but also increases workload.

It has been demonstrated that airline pilots prefer the MBC approach over MBE (Olson & Sarter, 1998), due to their ability to control system functions. However, pilot preference shifted to MBE in situations involving high workload, task complexity, and situations resulting in heightened time pressure.

Management by Exception

MBE is the management style that incorporates higher levels of automation. According to Billings (1996) management by exception is "a management-control situation in which the automation possesses the capability to perform all actions required for mission completion and performs them unless the manager takes exception". Essentially, this management style incorporates the use of levels 8 and 9 on Kaber & Endsley's (2003) level of automation taxonomies. This allows for the machine to initiate and perform functions on its own, and requires little pilot interaction (Billings, 1997); yet, the pilot still has the opportunity to become involved in system operations when chosen, or re-delegate tasks to automation when necessary.

MBE reduces the amount of pilot involvement and increases the risk of losing track of system functions. This management style also requires the pilot to perform a monitoring role, often resulting in automation surprises such as degraded SA and sporadic cognitive workload (Sarter, Woods, Billings, 1997). Automation problems are believed to be further exacerbated in systems that do not actively support operators in the monitoring role (Olson & Sarter, 2000).

The benefits of automation, especially on a grand scale, is likely indicative on the level of automation that is implemented (Mouloua, Gilson, Daskarolis-Kring, Kring, Hancock 2001; Parasuraman, et al., 2000). Much research is needed to determine which levels of automation are optimal for UAS operations (McCarley & Wickens, 2005). Ruff, Calhoun, Draper, Fontejon, and Guilfoos (2004) performed a similar UAS study that indicated MBE resulted in higher workload and poorer performance then MBC. A preceding study also discovered that MBC produced a higher level of mission efficiency and higher levels of SA than MBE (Ruff, Narayanan, & Draper, 2002). The known advantages and disadvantages of each management style are shown in Figure 8.

Level of Automation	**Advantages**	**Disadvantages**
Management by Consent (MBC)	• Involves human in action selection process • Greater Situation Awareness	• Higher levels of Operator workload • Longer action selection times
Management by Exception (MBE)	• Lower levels of operator workload • Shorter action selection times	• Removes human requirement from action selection • Prompts lower operator awareness

Figure 8. LOA Comparisons (Wasson, 2005)

Summary

The UAS control station must allow the pilot to fly the aircraft in a safe manner. Many of the human performance related regulations and standards related to human performance that exist today apply to the UAS control station but are not sufficient when the pilot is remote from the aircraft. A human centered control station design will mitigate human error and facilitate safe, easier control station training and learning.

-RTCA SC-203, 2007

UASs are complex highly-automated systems that intend to operate within expansive and rather unpredictable environments. While operating in these environments, they are restricted by human and technology limitations, as well as regulatory frameworks mandated for safe facilitation of the NAS. The unmanned aircraft component of the system must demonstrate an *equivalent level of safety* to that of manned aircraft. The pilot must be able to monitor and assess the state of the unmanned aircraft, the unmanned aircraft operating environment, as well as monitoring the control station environment. As a result, heightened cognitive demands that drastically alter mental workload and SA should be expected. A faulty human-control interface design can present grave danger to other NAS users if not properly engaged. Unfortunately, performance testing in this critical area is extremely rare and time is growing short.

There currently lacks a certifiable UAS design that has been granted access into the NAS by the FAA. Adequate standards and guidance material is currently being developed to help facilitate a safe and effective implementation of this aspiring technology. Though certification expectations for technology have yet to be identified, one thing remains certain: *the pilot remains to be the sole responsibility of the aircraft.* A new and refreshing design approach would be to use the human as a starting point, and design the automated machine as an extension of the pilot.

A main area of concern is to discover an ideal combination of KSAs in conjunction with automation strategies. It is pertinent that the pilot be delivered the right information, at the right time, and in the right manner. It is also important for the pilot to perceive that information correctly, make decisions based on sound rationale, and provide correct feedback. In the event that a lower level of autonomy is used, the pilot must be able to safely keep up with the cognitive workload while maintaining adequate SA. In the event that a higher level of automation is used, the pilot must still remain adequately involved, aware, and in-the-loop of the UAS operation. MBC and MBE automation strategies in conjunction with pilot and ATC expertise are all familiar attributes in the aviation domain. The intent of this current research is to discover a good combination between the management styles and individual experiences, rather than solely focusing on each factor individually. Therefore, both Air Traffic Controllers (with extrinsic flight familiarity) and pilots (with intrinsic flight familiarity) will be tested at both MBE and

MBC levels of automation to determine if there are any prominent combinations that exist.

Statement of Hypotheses

Hypothesis 1: Participants using MBC automation strategies will result in higher accuracy scores than those using MBE automation strategies.

Hypothesis 2: Participants using MBE automation strategies will result in lower task processing times than those using MBC automation strategies.

Hypothesis 3: Participants using MBE automation strategies will result in lower workload scores than when they are using MBC automation strategies.

Hypothesis 4: Participants using MBC automation strategies will result in higher SA scores than when they are using MBE automation strategies.

Hypothesis 5: The Pilot group will result in higher task accuracy scores than the ATC group and the control group.

Hypothesis 6: The ATC group will result in lower task processing times than the Pilot group and the control group.

Hypothesis 7: The ATC group will indicate lower workload scores than the Pilot group and the control group.

Hypothesis 8: The Pilot group will indicate higher SA scores than the ATC group and the control group.

Hypothesis 9: An interaction will exist between level of automation and user experiences for task processing times. Specifically, in high levels of automation, Air Traffic Controllers will have lower task processing times, whereas pilot task processing times will remain the same or increase.

Hypothesis 10: An interaction will exist between level of automation and user experiences for workload. Specifically, in high levels of automation, Air Traffic Controllers will indicate lower workload ratings, whereas pilot workload ratings will increase or remain the same.

Hypothesis 11: An interaction will exist between level of automation and user experiences for situation awareness. Specifically, in high levels of automation, Air Traffic Controllers will indicate lower situation awareness ratings, whereas pilot situation awareness ratings will increase or remain the same.

Method

Participants

Twenty-four participants from Embry-Riddle Aeronautical University were selected to participate in the study. All students were upper-classmen with an average age of 22 years. 16 students were male and 8 were female. The targeted population groups were inclusive of eight flight students, eight ATC students, and eight additional Human Factors students to represent the baseline. All participants were selected on a volunteer basis. Participants were asked to sign a consent form acknowledging their willingness to participate on a free-will basis (see Appendix A). Each volunteer was compensated $15 for their time. An additional $100 cash prize incentive was awarded to the top performer.

Apparatus

The apparatus consisted of a UAS software test-bed simulation device called MIIIRO (Multi-modal Immersive Intelligent Interface for Remote Operations). MIIIRO has been widely used as an UAS research simulator (Nelson, Lefebvre, & Andre, 2004;

Tso et al. 2003). The software was designed by IA Tech with support from the Air Force Research Laboratory, and is geared towards supporting research for long-range, high-endurance UASs. The hardware component is comprised of a standard PC with a dual monitor setup. The primary monitor portrayed the Tactical Situation Display (TSD) which encompassed the topographical image of the unmanned aircraft's environment, the unmanned aircraft(s), a color-coded assignment of unmanned aircraft routes, critical

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and SA were subjective measures filled out by the participants, whereas accuracy and response times were objective measures collected by the MIIRO software. Refer to table 4 for a graphical depiction of the experimental design.

Table 4

Experimental Design

		Experience		
		Pilot	ATC	Baseline
Level of Automation	MBC	8	8	8
	MBE			

Tasks

Primary Task

The MBC and MBE flight mission scenarios were set up similar to a highly-automated UAS. Therefore, there was no direct control of the unmanned aircrafts flight control surfaces. Instead, predetermined waypoints made up the flight path in which the unmanned aircraft autonomously followed. Along the flight path, 15 image capture locations were also preset and the associated images were automatically displayed to the participant, once the unmanned aircraft approached the preset waypoint.

The primary task of the participant was to view the images collected by the unmanned aircraft and verify that the Automatic Target Recognizer (ATR) had selected the correct target(s) present in the image. Each image collected along the flight route contained at least one ground vehicle, but a threat was not always present. The threats and non-threats were depicted as ground vehicles and were visually discernable by color, but were not always selected correctly by the ATR. The ATR attempted to distinguish between the two or more vehicles by placing a red box around the threat(s). The reliability of the ATR was set to 80%, so the participant had to verify that threats were correctly selected. In cases where the ATR had incorrectly dissociated threats from non-threats, the participant needed to manually select and/or deselect the images by directly clicking on the targets with a mouse curser.

During MBC scenarios, the participant processed the image manually by accepting or rejecting each image in the image cue. During MBE scenarios, the computer automatically processed the images after a 15 second duration, unless the participant overrode the automation by manually processing the images. If the participant needed more time, they were instructed to press a hold button which reset the time-out period to 15 seconds.

Primary task performance data was collected automatically by the MIIIRO software. The primary dataset was inclusive of: image response time, image queue time, image processing time, target selection accuracy, manual accepts/rejection, automatic accepts/rejections and image hold times.

Secondary Task

There are two secondary tasks associated with the experiment. The first task encompassed Intruder Aircraft (IA) events that mimicked an unexpected aircraft entering within the unmanned aircrafts airspace. This random event occurred twice per trial, and was deemed a highly critical situation that necessitated a quick and attentive response. The event was depicted by a red aircraft-shaped icon instantly appearing on the TSD at random times. To alleviate the threat, the participant needed to click on the aircraft and enter a pre-determined code.

The second task encompassed a MMI that mimicked an indicator representing the status or health of the UAS. This indicator was constantly displayed on the TSD and looked similar to a horizontal traffic light. It was made up of three round lights that changed from green to yellow or red, depending on the unmanned aircrafts status. A green status indicated that the unmanned aircraft was in good health. The light would randomly change to yellow or red, indicating that attention was needed from the simulated pilot to correct the situation. To correct the situation, the participant was required to click on the light panel and correctly type in a text string of numbers shown in a pop-up window. Once the text string was entered correctly, the status indicator returned back to green, indicating a healthy status.

Secondary task performance data was collected automatically by the MIIIRO software. The secondary dataset is inclusive of: MMI event occurrences, MMI response times, IA occurrences, and IA detection response times.

Subjective Workload

A NASA-TLX rating scale was used to measure workload experienced by the participants (Hart & Staveland, 1988). The NASA-TLX provided an overall workload score based on a weighted average and rating of six subscales: Mental Demands, Physical Demands, Temporal Demands, Performance, Effort, and Frustration. The participant first responded to a series of pair-wise comparisons to determine the *ranking* order in which each subscale topic contributed to overall workload during the task. These subscales were then weighted in order of its rank, with the top ranking subscale given the most weight. The participant then *rated* each workload subscale individually as to how they felt it pertained to the mission scenario. High ranking subscales did not always coincide with highly rated subscales. For example, the participant may have *ranked* the Physical Demand subscale to be the most critical aspect effecting workload, but still *rated* it low due to it being a computer-based simulation requiring little physical demands. Documentation of the NASA-TLX is provided in Appendix C.

Subjective Situation Awareness

A modified Post-Trial Participant Subjective Situation Awareness Questionnaire (PSAQ) was used to measure the level of SA experienced by the participants. The PSAQ instrument is a questionnaire designed for the participant to rate specific levels of SA and also illicit their own responses following each mission scenario. Each item was rated on a 5-point scale. A rating of 1 indicated that the participant was not aware of the evolving situation, whereas a rating of 5 indicated that the participant had been fully aware of the evolving situation (Strater, Endsley, Pleban, & Matthews, 2001).

The PSAQ derived from Strater et al. (2001) originally measured three items:

- Workload: how hard the participant worked during the scenario.
- Performance—how well the officer performed during the scenario, and
- Self-perceived SA—how aware the officer was of the evolving situation.

These three subjective measurements were retained for the questionnaire being conducted in this current study. However, an additional five questions were added to assess the participants' SA specific to events contained within each mission scenario. This is inclusive of the Mission Mode Indicator status, Intruding Aircraft, and the perception of the aircrafts involvement within the surrounding environment. The modified PSAQ questionnaire can be found in Appendix D.

Procedure

Upon the participant's arrival to the lab, they were asked to fill out a consent form (see Appendix A) and Biographical Questionnaire (see Appendix B) asking questions about their background. During this time, they were also introduced to the PSAQ and NASA-TLX questionnaires. The participants were then be familiarized with the MIIIRO simulator and informed of the research taking place. Each participant took part in an instructional session and a five-minute hands-on training exercise that familiarized them with all possible events that were to occur in the actual scenarios. Any questions that the participants had were answered at that time.

After the participant had been briefed and were ready to proceed, they were instructed to begin the trial. No assistance was granted at this time. Each participant conducted both MBC and MBE scenarios. In an effort to counterbalance the ordering effect, the first scenario was randomly assigned, followed by the alternate scenario. Accuracy and time data were automatically collected by the MIIIRO test bed software. Immediately following each simulated flying mission, the participant filled out a workload and SA questionnaire. Once both trials were complete, and all data was collected, the participant was debriefed and additional questions were answered at that time. Each participant was paid $15 for their participation and was instructed to sign a payment receipt. Once the entire study was concluded, the individual with the highest performance score was contacted and awarded $100.

Results

The objective of the present study was to investigate the effects of level of automation and user experience on UAS piloting performance, workload, and situation awareness. The achieved results have been divided into four main areas of interest: accuracy, task processing time, workload, and situation awareness. The data was analyzed using several repeated measure factorial designs to assess the effects of level of automation on user experience resulting in each of the following independent variables: image accuracy, image processing time, MMI processing time, IA processing time, workload, and situation awareness.

Accuracy

For the primary task, image accuracy refers to the number of images correctly accepted or rejected as being a threat or non-threat. The number of correctly processed images were then divided by the total number of images for each simulated mission to reveal an overall percentage score. Hypotheses one and five anticipated that the level of automation, and the experience levels of the simulated pilot would impact the task accuracy scores. Hypothesis one predicted that the use of MBC automation strategies would result in higher accuracy scores than the use of MBE automation strategies. Hypothesis five predicted that the Pilot group would result in higher task accuracy scores than the ATC group and the control group. To test these hypotheses, a repeated measures factorial ANOVA was conducted on the accuracy scores.

Image Accuracy

Table 5 illustrates the ANOVA results on image accuracy.

Table 5

ANOVA Source Table for Target Accuracy (%)

Source	SS	*df*	MS	*f*	*p*	Eta Squared	Power
Within Subjects							
LOA	.188	1	.188	.015	.902	.004	.052
LOA*Experience	.375	2	.188	.015	.985	.106	.052
Error (LOA)	255.938	21	12.188				
Between Subjects							
Intercept	437963.021	1	437963.021	4769.262	.000	.981	1.000
Experience	479.042	2	239.521	2.608	.097	.007	.462
Error	1928.438	21	91.830				

* $p < .05$.

Image Accuracy Main Effect Interpretation: Level of Automation. The derived F=.015 for the level of automation main effect did not exceed the tabled critical value F=4.33 at p=.05 with df_1=1 and df_2=21. Therefore, it is concluded that the mean image accuracy score for MBC (M=95.458, SD=8.387) was not significantly different from the mean image accuracy score for MBE (M=95.583, SD=6.743), $F(1,21)$=.015, p>.05. In terms of hypothesis one, it appears that the differences in image accuracy scores among the MBC and MBE groups are non-significant.

Image Accuracy Main Effect Interpretation: Experience. The derived F=2.608 for the experience main effect did not exceed the tabled critical value F=3.47 at p=.05 with df_1=2 and df_2=21. Therefore, it is concluded that there are no significant differences among the mean image accuracy scores for the Pilot (M=97.500, SD=3.665), ATC

(M=91.063, SD=11.51), and control (M=98.000, SD=2.58) groups, $F(1,21)=2.608$, $p>.05$. In terms of hypothesis five, it appears that the differences in image accuracy scores among Pilot, ATC, and control groups are non-significant.

Task Processing Time

Task processing times are separated into three individual times pertaining to three different tasks. The primary task, image processing time, represents the average time it took the simulated pilot to recognize and process the ground-based images displayed in the IMD. The MMI processing time represents the average time it took the simulated pilot to identify and accurately respond to the multiple mission mode indicator events. The IA processing times indicate the average time it took the simulated pilot to identify an intruder aircraft and resolve the conflict using the IFF code. Hypotheses two, six, and nine all refer to task processing times. Hypothesis two predicted that participants using MBE level of automation strategies would result in lower task processing times than participants using MBC levels of automation. Hypothesis six predicted that the ATC group would have lower task processing times than the Pilot group and the control group. Hypothesis nine predicted that an interaction would exist between the level of automation and user experience for task processing times. To test these hypotheses, a repeated measures factorial ANOVA was conducted on each of the processing times.

Image Processing Time

Table 6 illustrates the ANOVA results on image processing time.

Table 6

ANOVA Source Table for Image Processing Time (ms)

Source	SS	df	MS	f	p	Eta Squared	Power
			Within Subjects				
LOA	295945	1	295945	.515	.481	.024	.105
LOA*Experience	189348	2	94674	.165	.849	.015	.072
Error (LOA)	12061848	21	574375				
			Between Subjects				
Intercept	625933852	1	625966852	383.064	.000	.948	1.000
Experience	5197983	2	2598991	1.59	.227	.132	.298
Error	34316222	21	1634105				

* $p < .05$.

Image Time Main Effect Interpretation: Level of Automation. The derived F=.515 for the level of automation main effect did not exceed the tabled critical value F=4.33 at p=.05 with df_1=1 and df_2=21. Therefore, it is concluded that the mean image processing time for MBC (M=3532.708, SD=970.16) was not significantly different from the mean image processing time for MBE (M=3689.750, SD=1144.40), $F(1,21)$=.515, p>.05. In terms of hypothesis two, it appears that the differences in image processing times among the MBC and MBE groups are non-significant.

Image Time Main Effect Interpretation: Experience. The derived F=1.59 for the experience main effect did not exceed the tabled critical value F=3.47 at p=.05 with df_1=2 and df_2=21. Therefore, it is concluded that there are no significant differences among the mean image processing times for the Pilot (M=4072.500, SD=1403.55), ATC

(M=3327.125, SD=865.54), and control (M=3434.062, SD=728.17) groups, $F(2,21)=1.59$, $p>.05$. In terms of hypothesis six, it appears that the differences in image processing times among Pilot, ATC, and control groups are non-significant.

Image Time Interaction Interpretation: Level of Automation by Experience. The derived $F=.165$ for the level of automation x experience interaction did not exceed the tabled critical value $F=3.47$ at $p=.05$ with $df_1=2$ and $df_2=21$. Therefore, it is concluded that the interaction between the level of automation and experience levels on image processing times is non-significant, $F(2,21)=.165$, $p>.05$. In terms of hypothesis nine, it appears that the interaction between the level of automation and the experience levels on image processing times is non-significant.

MMI Processing Time

Table 7 illustrates the ANOVA results on MMI processing time.

Table 7

ANOVA Source Table for MMI Processing Time (ms)

Source	SS	df	MS	f	p	Eta Squared	Power
			Within Subjects				
LOA	572033	1	572033	.391	.539	.018	.092
LOA*Experience	2285095	2	1142547	.780	.471	.069	.165
Error (LOA)	30742643	21	1463935				
			Between Subjects				
Intercept	3272909670	1	3272909670	374.437	.000	.947	1.000
Experience	3045872	2	1522936	.174	.841	.016	.074
Error	183558423	21	8740877				

*p < .05.

MMI Main Effect Interpretation: Level of Automation. The derived $F=.391$ for the level of automation main effect did not exceed the tabled critical value $F=4.33$ at $p=.05$ with $df_1=1$ and $df_2=21$. Therefore, it is concluded that the mean MMI processing time for MBC (M=8366.625, SD=2331.85) was not significantly different from the mean MMI processing time for MBE (M=8148.292, SD=2027.73), $F(1,21)=.391, p>.05$. In terms of hypothesis two, it appears that the differences in image processing times among the MBC and MBE groups are non-significant.

MMI Main Effect Interpretation: Experience. The derived $F=.174$ for the experience main effect did not exceed the tabled critical value $F=3.47$ at $p=.05$ with $df_1=2$ and $df_2=21$. Therefore, it is concluded that there are no significant differences among the mean MMI processing times for the Pilot (M=8612.625, SD=3078.55), ATC (M=8055.875, SD=1530.19), and control (M=8103.875, SD=1799.37) groups, $F(2,21)=.174, p>.05$. In terms of hypothesis six, it appears that the differences in MMI processing times among Pilot, ATC, and control groups are non-significant.

MMI Interaction Interpretation: Level of Automation by Experience. The derived $F=.780$ for the level of automation x experience interaction did not exceed the tabled critical value $F=3.47$ at $p=.05$ with $df_1=2$ and $df_2=21$. Therefore, it is concluded that the interaction between the level of automation and experience levels on MMI processing times is non-significant, $F(2,21)=.780, p>.05$. In terms of hypothesis nine, it appears that the interaction between the level of automation and the experience levels on MMI processing times is non-significant.

IA Processing Time

Table 8 illustrates the ANOVA results on IA processing time.

Table 8

ANOVA Source Table for IA Processing Time (ms)

Source	SS	df	MS	f	p	Eta Squared	Power
			Within Subjects				
LOA	3884563	1	3884563	.910	.351	.042	.149
LOA*Experience	21439361	2	10719680	2.512	.105	.193	.447
Error (LOA)	89614478	21	4267356				
			Between Subjects				
Intercept	2502466449	1	250246649	107.237	.000	.836	1.000
Experience	66253778	2	33126889	1.420	.264	.119	.270
Error	490050601	21	23335742				

*p < .05.

IA Main Effect Interpretation: Level of Automation. The derived F=.910 for the level of automation main effect did not exceed the tabled critical value F=4.33 at p=.05 with df_1=1 and df_2=21. Therefore, it is concluded that the mean IA processing time for MBC (M=7504.917, SD=4368.12) was not significantly different from the mean IA processing time for MBE (M=6935.958, SD=3152.00), $F(1,21)$=.910, p>.05. In terms of hypothesis two, it appears that the differences in IA processing times among the MBC and MBE groups are non-significant.

IA Main Effect Interpretation: Experience. The derived F=1.420 for the experience main effect did not exceed the tabled critical value F=3.47 at p=.05 with df_1=2 and df_2=21. Therefore, it is concluded that there are no significant differences among the mean IA processing times for the Pilot (M=8878.625, SD=5808.26), ATC (M=6300.563, SD=2143.88), and control (M=6482.125, SD=2384.19) groups, $F(2,21)=1.420, p>.05$. In terms of hypothesis six, it appears that the differences in IA processing times among Pilot, ATC, and control groups are non-significant.

IA Interaction Interpretation: Level of Automation by Experience. The derived F=2.512 for the level of automation x experience interaction did not exceed the tabled critical value F=3.47 at p=.05 with df_1=2 and df_2=21. Therefore, it is concluded that the interaction between the level of automation and experience levels on AI processing times is non-significant, $F(2,21)=2.512, p>.05$. In terms of hypothesis nine, it appears that the interaction between the level of automation and the experience levels on AI processing times is non-significant.

Subjective Workload

Workload was measured subjectively using the NASA-TLX workload rating scale. Hypotheses three, seven, and ten refer to workload. Hypothesis three predicted that MBE automation strategies would result in lower workload scores than MBC automation strategies. Hypothesis seven predicted that the ATC group would result in lower workload scores than the Pilot group and the control group. Hypothesis ten predicted that an interaction would exist among the level of automation and the user experience groups for workload. To test these hypotheses, a repeated measures factorial ANOVA was conducted on the workload dependent variable.

Subjective Workload Results

Table 9 illustrates the ANOVA results on subjective workload.

Table 9

ANOVA Source Table for Workload

Source	SS	*df*	MS	*f*	*p*	Eta Squared	Power
			Within Subjects				
LOA	6.750	1	6.750	.047	.831	.002	.055
LOA*Experience	324.125	2	162.062	1.121	.345	.096	.220
Error (LOA)	3037.125	21	144.625				
			Between Subjects				
Intercept	70074.083	1	700074.083	149.107	.000	.877	1.000
Experience	3180.792	2	1590.396	3.384	.053	.244	.573
Error	9869.125	21	469.958				

*$p < .05$.

Workload Main Effect Interpretation: Level of Automation. The derived F=.047 for the level of automation main effect did not exceed the tabled critical value F=4.33 at p=.05 with df_1=1 and df_2=21. Therefore, it is concluded that the mean workload scores for MBC (M=37.833, SD=16.88) was not significantly different from the mean workload scores for MBE (M=38.583, SD=20.70), $F(1,21)$=.047, p>.05. In terms of hypothesis three, it appears that the differences in workload scores among the MBC and MBE groups are non-significant.

Workload Main Effect Interpretation: Experience. The derived F=3.384 for the experience main effect did not exceed the tabled critical value F=3.47 at p=.05 with df_1=2 and df_2=21. Therefore, it is concluded that there are no significant differences among the mean IA processing times for the Pilot (M=26.938, SD=19.84), ATC (M=45.875, SD=17.10), and control (M=41.812, SD=11.54) groups, $F(2,21)=3.384, p>.05$. In terms of hypothesis seven, it appears that the differences in workload scores among Pilot, ATC, and control groups are non-significant.

Workload Interaction Interpretation: Level of Automation X Experience. The derived F=1.121 for the level of automation x experience interaction did not exceed the tabled critical value F=3.47 at p=.05 with df_1=2 and df_2=21. Therefore, it is concluded that the interaction between the level of automation and experience levels on workload scores is non-significant, $F(2,21)=1.121, p>.05$. In terms of hypothesis ten, it appears that the interaction between the level of automation and the experience levels on workload scores is non-significant.

Subjective Situation Awareness

SA was measured subjectively using the PSAQ questionnaire. Hypotheses four, eight, and eleven refer to SA. Hypothesis four predicted that MBC automation strategies would result in higher SA scores than MBE automation strategies. Hypothesis eight predicted that the Pilot group would result in higher SA scores than the ATC group and the control group. Hypothesis eleven predicted that an interaction would exist between the level of automation and experience levels for SA. To test these hypotheses, a repeated measures factorial ANOVA was conducted on the SA dependent variable.

Subjective Situation Awareness Results

Table 10 illustrates the ANOVA results on subjective situation awareness.

Table 10

ANOVA Source Table for Situation Awareness

Source	SS	df	MS	f	p	Eta Squared	Power
			Within Subjects				
LOA	.013	1	.013	.086	.772	.004	.059
LOA*Experience	.366	2	.183	1.245	.308	.106	.241
Error (LOA)	3.082	21	.147				
			Between Subjects				
Intercept	834.667	1	834.667	1109.228	.000	.981	1.000
Experience	.118	2	.059	.078	.925	.007	.060
Error	15.802	21	.752				

*p < .05.

SA Main Effect Interpretation: Level of Automation. The derived F=.086 for the level of automation main effect did not exceed the tabled critical value F=4.33 at p=.05 with df_1=1 and df_2=21. Therefore, it is concluded that the mean workload scores for MBC (M=4.154, SD=.600) was not significantly different from the mean workload scores for MBE (M=4.186, SD=.694), $F(1,21)$=.086, p>.05. In terms of hypothesis four, it appears that the differences in SA scores among the MBC and MBE groups are non-significant.

SA Main Effect Interpretation: Experience. The derived F=.078 for the experience main effect did not exceed the tabled critical value F=3.47 at p=.05 with df_1=2 and df_2=21. Therefore, it is concluded that there are no significant differences among the mean IA processing times for the Pilot (M=4.136, SD=.616), ATC (M=4.240, SD=.584), and control (M=4.134, SD=.777) groups, $F(2,21)=.078$, $p>.05$. In terms of hypothesis eight, it appears that the differences in SA scores among Pilot, ATC, and control groups are non-significant.

SA Interaction Interpretation: Level of Automation X Experience. The derived F=1.245 for the level of automation x experience interaction did not exceed the tabled critical value F=3.47 at p=.05 with df_1=2 and df_2=21. Therefore, it is concluded that the interaction between the level of automation and experience levels on SA scores is non-significant, $F(2,21)=1.245$, $p>.05$. In terms of hypothesis eleven, it appears that the interaction between the level of automation and the experience levels on SA scores is non-significant.

Overall, the results indicate that there are no significant differences found among level of automation, experience, or an interaction thereof.

Discussion

The objective of this study was to analyze the effects of level of automation and the type of prior experience a simulated pilot has on UAS operations in the areas of performance and perception. Accuracy and time performance were both measured objectively, while workload and situation awareness were measured subjectively. In other words, the study intended to see if different experiences in the aviation domain attributed to better performance and SA while acting as a pilot-in-command of an UAS simulator. Varying levels of automation were also used to determine whether users with specific KSAs performed in a more cooperative and coordinated manner when combined with a specific automation level. The results of the study were divided into four areas of focus:

image accuracy, task processing time, subjective workload, and subjective situation awareness.

Image Accuracy

Image accuracy scores were collected automatically from the MIIIRO software. Image accuracy scores were calculated by determining the number of correctly processed images divided by the total number of images presented in each mission scenario. An image was correctly processed if the image is accepted when a 'threat target' is present, and if the image is rejected when there are no 'threat targets' in the image. Additionally, the accuracy of the Automatic Target Recognizer (ATR) was set to 80%. Therefore, automation would correctly designate the targets as threats/non-threats 80% of the time. The image processing task was deemed as the primary task.

The results of the image accuracy scores did not indicate any significant differences, regardless of the level of automation, or the experience level of the participant. The lack of significance was in contrast to hypothesis one and five. The results found in this current study indicate that the accuracy rate was 95% for MBC and 96% for MBE, with a SD of 8.4% and 6.7% respectively. This implies that if the participant relied solely on automation during the MBE mission scenario, they would reside outside one standard deviation of the mean. With the same ATR accuracy rate of 80%, Wasson (2005) found slightly lower results during the same two mission scenarios with a MBC and MBE accuracy percentage of 89% and 88% respectively, which is ultimately an average decrease of 2 out of the 30 images presented to the simulated pilot. A comparison of the results are displayed in figure 10.

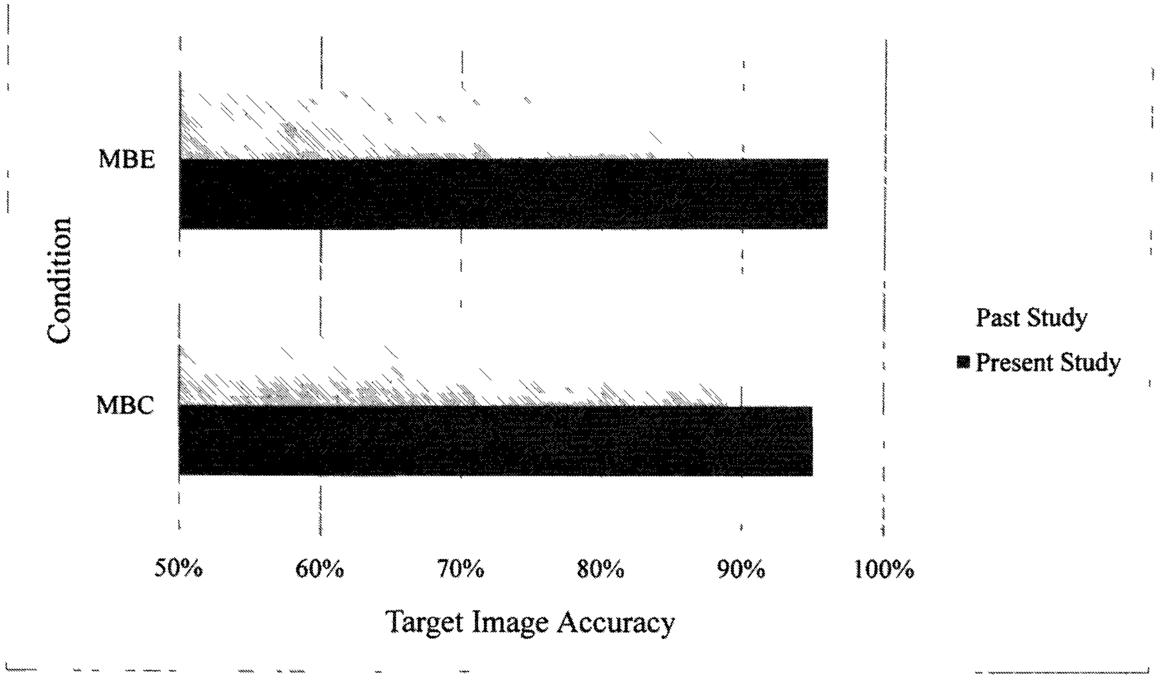

Figure 10. Comparison chart of task times for similar mission scenarios (data extracted from Wasson, 2005)

Subjective feedback obtained from the PSAQ questionnaire highlighted several factors that may contribute to a non-significant difference among the image accuracy means among prior experience and levels of automation. First, the majority of the images were easily deciphered at first glance, while a select few were rather obscure in detail. In other words, it was easy to distinguish the threats from the non-threats in the vast majority of the images. Yet a few of the images left very little evidence to distinguish between the targets, no matter how long the image was observed. For the non-obvious images, it was more of a guessing game, rather than a need to further analyze the image. Therefore, a quick decision and response could be made at first glance. Some participants revealed that even in cases where there was minimal doubt, they would not risk targeting a 'friendly', or non-threat. This type of rationale was never anticipated by the author of this research, but possibly played a significant role in the outcome of the accuracy scores.

More details on this issue will be discussed in the *Recommendations for Future Research* section.

Task Processing Time

Image Processing Time. Task processing times were collected automatically by the MIIIRO software. The image processing time pertains to the average amount of time it took for a participant to respond and fully process an image, by discerning 'threat' vehicles from 'non-threat' vehicles. The results of these image processing times did not indicate any significant differences, regardless of the level of automation, or the experience level of the participant. This is in contrast to hypotheses two, six, and nine. Past research has suggested that image processing times were higher during the MBE level of automation, due to the participant relying on automation to process the image in a minimum of 15 seconds. Using an identical mission scenario, Wasson (2005) indicated that participants processed images at an average rate of 4564ms for MBC and 5965ms for MBE, whereas the results in this current study indicate that participants processed images at an average rate of 3533ms for MBC and 3689ms for MBE. A reasonable explanation for the faster processing times may be that there was a large monetary incentive for the top performer in speed and accuracy of the primary task. An alternative explanation for the faster processing times could be due to the targeted groups of participants selected in this study to satisfy the levels of experience criteria. Additionally, the MBE option was very rarely used among participants. In fact, data collected by the MIIIRO software indicated that the most it was ever used by any single participant was once. Ruff et. al. (2004) pointed out that participant's typically responded to images rather than allowing automation to process them. This finding is also supported by Olson & Sarter (1998), specifically among experienced pilots conducting flight tasks under MBC/MBE strategies. This study found that all three levels of experience (pilot, ATC, and control group) chose to process the images on their own, rather than rely on MBE strategies.

MMI Processing Time. There were also two secondary task processing times collected automatically by the MIIIRO software: MMI times, and IA times. Essentially, each of these tasks competed for the same mental resources as the primary task. The MMI times reflect the amount of time it took a participant to become aware of an abnormal MMI indication of yellow or red (indicating a need for a response), and respond to it by clicking directly on the indicator and typing in a string of numbers displayed in the resulting pop-up box. The results of these MMI processing times did not indicate any significant differences, regardless of the level of automation, or the experience level of the participant. This is in contrast to hypotheses two, six, and nine. These results concur with Wasson's (2005) study, where the average MMI processing times were 8926ms for MBC and 10996ms for MBE, whereas the results in this current study indicate that participants processed images at an average rate of 8367ms for MBC and 8148ms for MBE. Once again, the faster processing times may be attributed to the monetary incentive for the top performer in the primary task (despite this was not part of the primary task).

IA Processing Times. The IA times reflect the amount of time it took a participant to become aware of IA, and respond to it by clicking directly on the IA icon and typing in the revealed code 'daytona' in the resulting pop-up box. The results of the mean IA processing times did not indicate any significant differences, regardless of the level of automation, or the experience level of the participant. This is in contrast to hypotheses two, six, and nine. These results concur with Wasson's (2005) study, where the average IA processing times were 8752ms for MBC and 7997ms for MBE, whereas the results in this current study indicate that participants processed images at a faster average rate of 7505ms for MBC and 6936ms for MBE. Once again, the faster processing times may be attributed to the monetary incentive for the top performer in the primary task (despite this was not part of the primary task).

Overall, these results suggest that the differences in mean processing times among the primary and secondary tasks were non-significant among both the level of automation and the prior experiences of the participant groups. It is noteworthy that response times are indicative of adequate SA, alertness, scanning abilities, and responses times, yet two out of three of the quickest responders were among the control group, having no flight or ATC experience. Additionally, the top two fastest responders were the only participants who indicated computer gaming experience beyond the '0-5 hour' choice in the biographical questionnaire. In both cases the highest choice of '20-25+' hours of computer gaming per week was selected.

Subjective feedback obtained from the PSAQ questionnaire revealed several theories as to why task processing times were comparatively quick. First, participants indicated that the overall mission was simple enough to quickly detect and react to all three timed events. The image processing task was deemed easily mediated, as any additional time spent on the task would not alter the initial decision of deciphering 'threats' from 'non-threats'. Additionally, unlike the MMI, the IA was easily recognizable since it instantly appeared as a "bright red blip" on the display. The MMI was said to be a bit trickier, since all three lights were continuously present, and the changes in brightness were harder to detect. Perhaps, if the primary task was more complex and required more time to process, than all three task times would have been increased. On the other hand, participants acknowledged that it was difficult to stay focused on the mission, and often felt as if they were just responding to event occurrences rather than actually processing information and making decisions. It was often revealed that the cash incentive of $100 for being the top performer encouraged quick and attentive responses. This notion is supported by comparing the task response times with a former between-subjects study using an identical mission scenario, with a $20 incentive prize. An overview of the task times comparing the two studies are displayed in figure 11. An alternate theory may suggest that the time differences were due to the addition of the targeted experience levels presented in this study.

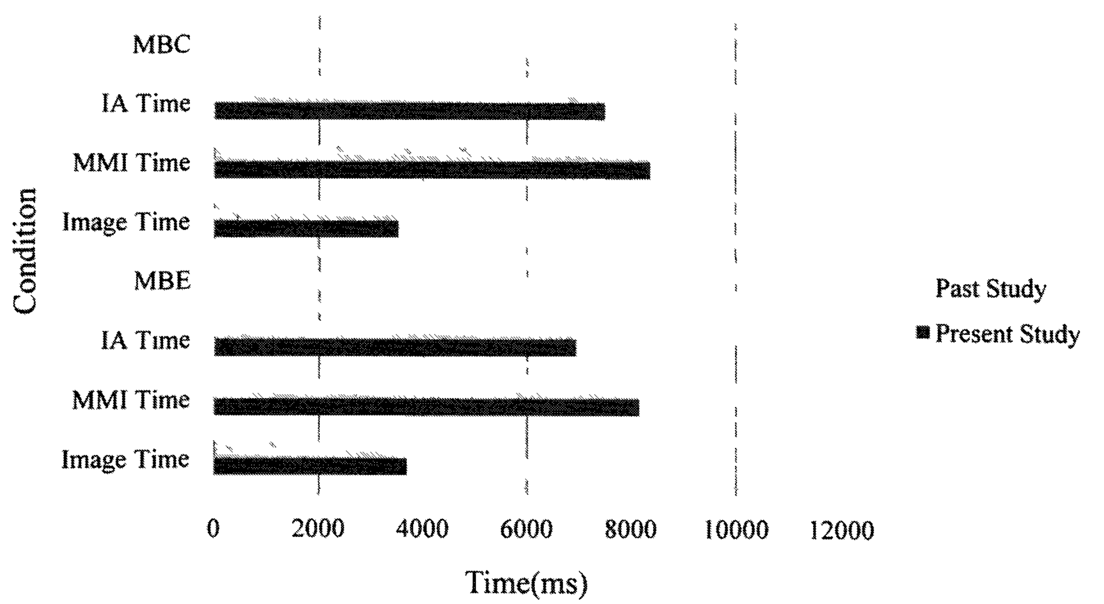

Figure 11. Comparison chart of task times for similar mission scenarios (data extracted from Wasson, 2005)

Subjective Workload

The NASA-TLX workload assessment was introduced to the participant prior to the training session. It was then described in greater detail and completed by the participant following each mission. The results of the mean workload scores did not indicate any significant differences, regardless of the level of automation, or the experience level of the participant. This is in contrast to hypotheses three, seven, and ten.

Past studies reveal that the Modified Cooper-Harper scale may not have been sensitive of specific enough to analyze workload on the MIIIRO simulator (Wasson, 2005; Ruff et al., 2004). Therefore, the NASA-TLX was used for this study. A statistical analysis revealed that the significance level among the three levels of experience was .052 with a power level of .573. The mean workload score of the pilot group was 27, in comparison to the mean workload scores of ATC and control groups of 46 and 42, respectively. Yet, each participant experienced the same exact mission scenarios. This supports the notion that there were few differences that existed between the MBC and MBE mission scenarios. In other words, if the participant ignores the automated capabilities that are offered during the MBE mission scenario, then they are essentially performing the same mission as if they were operating under MBC strategies. The two mission scenarios were nearly identical, with the addition of MBE capabilities. Since both levels of automation were performed by each participant, there was opportunity for each participant to rate one scenario above the other, but this was not the case. Furthermore, the only workload measure that came close to showing any significance was a result of the pilot group indicating lower workload scores than the ATC and control groups, despite performing the same mission scenarios. It is a possibility that a pilot's perception of workload under the tested conditions are in direct comparison to actually flying an aircraft, whereas no other tested group can make this comparison.

Subjective Situation Awareness

A modified PSAQ questionnaire was introduced to the participant prior to the training session. It was then described in greater detail and completed by the participant following each mission. The results of the mean SA scores did not indicate any significant differences, regardless of the level of automation, or the experience level of the participant. This is in contrast to hypotheses four, eight, and eleven.

It became apparent during the literature review that measuring SA while measuring workload could be beneficial. Often times, while working with automation, workload may decrease but also result in SA decrements. Therefore, the PSAQ questionnaire was modified to evaluate participant SA in several areas and tasks related to the simulated mission scenarios. This also presented an opportunity to gain participant feedback over all areas of the experiment.

Differences in SA appeared to be non-significant among all tested groups. A possibility for these results is due to the inability for the participant to get any feedback on their performance. In most cases, if the participant missed an MMI or IA event, they remained unaware of doing so. The participants were never aware of their performance in the primary and secondary tasks nor did they have a foundation to base their performance on. Simply put, they were not aware of what they weren't aware of. Indicated SA scores remained high across all participants, regardless of their actual performance.

The feedback section in the PSAQ questionnaire was useful in determining how participants perceived the mission scenario. For instance, it was common for participants to mention how the IA events were much more recognizable than the MMI events. Other participants mentioned how they neglected to pay attention to the majority of the Tactical Situation Display, since all tasks could be accomplished by focusing on the uppermost section of the display. As a result, attention was completely detracted from the aircraft in accordance with its location on the map. Participants also advised that their performance was not degraded due to lack of attention, but because the events often took place all at once, forcing them to prioritize which tasks to respond to first. It was common for a participant to reveal that they remained attentive primarily due to the monetary incentive or the "challenge" posed against the other groups. SA results may have varied without the cash incentive or the competition, as both were compelling characteristics of the experiment. Additionally, adding the MBE option on the primary task seemed to add another element that most participants thought was more of a nuisance than a help. Lastly, participants indicated that the tasks were too simple and became boring.

Overall, the experiment did not reveal any significant differences among level of automation and user experience levels.

Study Limitations

The primary constraint that incurred throughout this study was the simulation test-bed design. Although this research did not detect any significant differences among the KSAs of individual experiences, it can be reasonably theorized that differences still exist. It became apparent during the experiment that participants acted more as responders rather than troubleshooters. This was partly due to the task requirements implemented in the design. The design relied on the scanning capabilities and response times of the participants, rather than extensive decision making, troubleshooting, or strategizing abilities. This ultimately relieved the participants from having to perform with the use of prior knowledge and training. Thus, knowledge played an insignificant role, yet it is the knowledge-base that ultimately separates the participants among the three experience groups. A more appropriate setup would have required a testbed design that allowed for the participant to interact more as an operator, rather than a monitor. This would allow the simulated pilots to further exploit his/her knowledge base, specifically in the areas of detect, sense and avoid (DSA), operating procedures, and troubleshooting lost communications. However, the real-world role of a UAS operator is still unknown, and a certifiable user-interface has yet to be discovered.

Additionally, the MBC and MBE settings for either particular mission scenario did not make any significant changes. It may be advantageous if these individual settings resulted in more extreme differences. Overall, the mission scenarios were too simple, and the level of automation did not play a large factor in performance. The overall complexity of the mission was too easy and required minimal mental processing ability to complete. There are a variety of UASs, and the option of user-interfaces are vast. Fixating on a highly automated and restrictive testbed may ultimately restrict research potential. It would be beneficial to invest in a testbed that allows for more design flexibility and capabilities.

The primary task associated with the processing images did not require much time or mental processing to accomplish. The images used in this study were purposely set at a very low resolution in an effort to require the participant to spend more time analyzing it.

However, participants were still capable of making processing decisions at first glance. In other words, looking at the image longer did not alter their level of certainty in distinguishing threats from non-threats. Perhaps a new set of images would have made this task more appropriate for distinguishing experience characteristics. This issue will be discussed more in the *Recommendations for Future Research* section of this report. Furthermore, during the MBE scenarios, the time-out period for automatic image processing was 15 seconds. This provided ample time for the participant to process the image on their own. Perhaps, if the time-out period was reduced, participants would have relied more on the higher level of automation to assist them with the primary task.

The sample population used in this study may have played a contributing factor in the lack of differences among participants with varying expertise and experiences. All participants were relatively inexperienced, when compared to individuals who have worked in the respective professions for several years. Due to financial and time constraints, it was infeasible to acquire well-experienced participants for this particular study. Furthermore, the sample size was relatively small, mainly due to money and time constraints, but also due to the timing in which the experiment took place. All of the participants were selected during the summer months, thereby reducing the population size. However, in order to obtain a reasonable power size, statistical power calculations revealed that it probably would have required a much larger sample size than what would have been feasible for this type of research.

It is evident that a pilot study would have been useful in directing the outcome of the current research. The intent of the author was to apply a new independent variable (i.e. Experience), to a past research design (see Wasson, 2005) in order to determine if piloting or air traffic control experience may have played a significant role in their findings. If a pilot study was conducted prior to the current research, than the outcome of this study may have been foreseen, and modifications could have been made to allow for a more appropriate approach in determining the impact of experience on UAS piloting ability. Nevertheless, it may still hold true that significant difference in UAS piloting abilities are not reliant on the prior experience levels tested.

Practical Implications

This research is the first of its kind at an attempt to distinguish personal differences among potential UAS pilots with various backgrounds. Although no significant differences were discovered, this research can be used as a good starting point for setting up future testbeds to better analyze individual characteristics.

Current UAS designs are vast, and new concepts and innovations continue to unveil. Much research is still needed to uncover how automation strategies should be implemented in a system design, as well as the necessary skillsets required on behalf of the PIC. Does piloting experience play an issue in UAS operations? Will shared-fate alter decision making if the pilot is not co-located with the aircraft? There are still several questions left unanswered and should be figured out in a lab rather than being answered at the expense of human lives in the air or on the ground. By nature, UAS interface laboratory testing can simulate just about every scenario that can be experienced in actual operations.

Recommendations for Future Research

UAS research offers a wide variety of testing options that can essentially replicate real-world operations. Based on this current study, it would be advisable to further investigate options that are allowed by the MIIIRO software. This current research was an extension of two mission scenarios that were designed in a prior study in order to make direct comparisons of the results, with the addition of using targeted populations. It was discovered that the level of automation played a very small role in altering the involvement of the participant.

Additionally, emphasis should be directed on the primary task images. The current images require little time and effort to process. A different approach may be to collect birds-eye imagery from a source, such as Google Earth, that require the participant to scan and locate and designate specific items (such as basketball courts, swimming pools, or landing strips). This will eliminate the unnecessary decision to target threats from non-threats. Participant feedback in this study suggested that some users based their decision around whether to risk the lives of friendly targets. It will also require the simulated pilot to filter out an abundance of 'noise' in order to locate specific targets. Furthermore, this type of task will always remain open-ended, meaning the pilot in command will always have some level of doubt as to whether all targets are discovered and if the image should be accepted or rejected. In using this type of imagery, pilots, for instance, may have a higher confidence level in processing these images, due to their flight experience.

Research should also examine how various levels of expertise perform tasks related to in-flight planning, especially in the area of unexpected events. The current study examined how a participant would respond to known and foreseen events. They merely needed to respond to these events, rather than make think critically and make decisions. If this type of thinking was all that was needed in the realm of aviation, than pilots and controllers would not require much training. In fact, these unforeseen challenges in an ever-changing airspace environment is why it is so imperative that the human component remain in-the-loop of the system operation. Significant differences may be discovered among various user experiences if the missions allow additional flexibility for the user to become more involved in the actual mission (i.e. re-route aircraft around weather and traffic in order to complete a series of tasks).

Subjective workload and SA should be investigated further, perhaps objectively. It is also recommended that these measurements take place during extremely demanding situations requiring a high level of user involvement, as well as relatively boring situations requiring low levels of user involvement. It is also advisable to apply workload and SA ratings on specific tasks, rather than the overall mission. This will allow researchers to discern between tasks that lessen workload while maintaining or increasing SA.

Lastly, it is worth reiterating that the top performer in this study was among the baseline group and had no prior aviation training. The top two performers in the study were the only participants who indicated on the biographical questionnaire that they are avid computer gamers. The third top performer was neither a computer gamer, nor had prior aviation training, but used a computer more hours per week than any other participant. Future research may want to investigate whether computer familiarity plays an important role in conducting UAS operations from a PC-based operating platform.

Conclusion

UASs are on the verge of taking flight alongside manned counterparts. In fact, their presence in the military arsenal is well known and admired for their superior capabilities. Several other entities have witnessed the expansive opportunities that UASs have to offer, and are seeking ways to exploit this technology. However, regulatory constraints will not permit UAS operation in the NAS until technological constraints and human factors concerns have been overcome. Removing the human component from the flying platform poses several advantages, but does not come without an abundance of risk.

This study has initiated a much needed area of research pertaining to the user-interface design, as well as understanding the capabilities and KSAs required on behalf of the pilot. Unfortunately, no significant differences were determined among the experience levels of the simulated pilot, nor the level of automation that was implemented into the system design. The possibility of replicating realistic, real-world UAS operations in a laboratory setting should be enough motivation to further this type of research in a simulated environment, rather than allowing shortfalls to be discovered at the expense of human life.

The results discovered in this study revealed that humans, regardless of prior training in aviation realms, can perform substantially well under foreseen and expected circumstances. However, pilots are expected to remain in-the-loop of UAS operations for reasons that automation cannot mediate- the unforeseen, unexpected, and unintended situations. It is for this reason that future research should be carried out in these areas to determine the best approach at aligning adequate UAS pilots with an appropriately level of automation in an effort to promote coordinated team-play.

References

AIR-160. (2008, March 13). *Interim Operational Approval Guidance 08-01: Unmanned Aircraft Systems Operations in the National Airspace.* Washington, DC: Federal Aviation Administration.

ASTM F-2395-07, (2007). *Standard Terminology for Unmanned Air Vehicle Systems.* West Conshohocken, PA: ASTM International, 2007.

BAE Systems. (2007, November 7). *Unmanned Air System Project For South Coast Formally Launched.* BAE News Release. Retrieved August 31, 2009, from http://www.baesystems.com/Newsroom/NewsReleases/2007/autoGen_107107111943.html

Bainbridge, L. (1983). Ironies of automation. *Automatica*, 19, 775-779.

Barnes, M.J., & Matz, M. (1998). Crew simulation for unmanned aerial vehicles applications: Shift factors, interface issues and crew size. *Proceedings of the human factors and ergonomics society 42nd annual meeting*, pp. 143-148.

Batkiewicz, T.J., Dohse, K.C., Kalivarapu, V., Dohse, T., Walter, B., Knutzon, J., Parkhurst, D., Winer, E., & Oliver, J. (2006). Multimodel UAV ground control system, *11th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, Portsmouth, VA, AIAA 2006-6963, 6 September 2006.

Billings, C.E. (1996). *Human-centered aviation automation: Principles and guidelines (NASA Technical Memorandum 110381).* Moffet Field, CA: NASA Ames Research Center.

Billings, C. E. (1997). *Aviation automation: The search for a human centered approach.* Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Brinkerhoff, N. (2009). *Air force graduates first class of drone pilots.* Retrieved August 30, 2009, from http://www.allgov.com/ViewNews/Air_Force_Graduates_First_Class_of_Drone_Pilots_90612

Carmody, M.A., & Gluckman, J.P. (1993). Task specific effects of automation and automation failure on performance, workload and situation awareness. In: Jensen, R.S., & Neumeister D. (Eds), *Proceedings of the Seventh International Symposium on Aviation Psychology* (pp. 167-171). Columbus, OH: Department of Aviation, The Ohio State University.

Crescenzio F.D., Miranda G., Periani F., Bombardi T. (2007). Advanced interface for UAV ground control station. Proceedings of the AIAA *Modeling and simulation Technologies Conference and Exhibit*, Hilton Head, SC, AIAA 2007-6566, 23 August 2007.

DeGarmo, M., & Maroney, D. (2008). NEXTGEN and SESAR: opportunities for UAS integration. *Proceedings of the 26th Congress of International Council of the Aeronautical Sciences*, Anchorage, AK, AIAA 2008-8925, 19 September 2008.

Department of Defense. (2003). *Unmanned aerial vehicle reliability study.* Washington, DC: Department of Defense. Retrieved August 31, 2009 from http://www.acq.osd.mil/uas/

Department of Defense. (2005). *Unmanned aerial vehicles roadmap, 2005-2030.* Washington, DC: Office of the Secretary of Defense.

Department of Defense. (2009). *FY2009-2034 unmanned systems integrated roadmap.* Washington, DC: Office of the Secretary of Defense. Retrieved August 31, 2009 from http://www.acq.osd.mil/uas/docs/UMSIntegratedRoadmap2009.pdf

Dixon, S.R., Wickens, C.D., & Chang, D. (2003). Comparing quantitative model predictions to experimental data in multiple-UAV flight control. *Proceedings of the 47th human factors and ergonomics society,* 104-108.

EiBfeldt, H., & Heintz, A. (2002). Ability requirements for DFS controllers- current and future. In EiBfeldt, H., Heil, M., & Broach D. (2002). *Staffing the ATM System: The Selection of Air Traffic Controllers* (pp. 13-24), Aldershot, UK: Ashgate Publishing.

Endsley, M.R. (1987). The application of human factors to the development of expert systems for advanced cockpits, in *Proceedings of the Human Factors Society 31st Annual Meeting* (pp. 1388-1392). Santa Monica, CA.

Endsley, M.R. (1988). Design and evaluation for situation awareness enhancement, in *Proceedings of the Human Factors Society 32nd Annual Meeting* (pp. 97-101). Santa Monica, CA.

Endsley, M.R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors, 37*(1), 32-64.

Endsley, M.R. (1996). Automation and situation awareness. In R. Parasuraman & M. Mouloua (Eds.), *Automation and human performance: Theory and applications* (pp. 163–181). Mahwah, NJ: Erlbaum.

Endsley, M.R. (1997). Situation Awareness, Automation, & Free Flight, *1st USA/European Air Traffic Management R&D Seminar*, Sacley, France, June, 1997.

Ensley, M.R., & Kaber, D.B. (1997). The use of level of automation as a means of alleviating out-of-the-loop performance problems: a taxonomy and empirical analysis, in Seppala, P., Luopajarvi, T., Nygard C.H., & Mattila, M. (eds), *13th Triennial Congress of the International Ergonomics Association*, Vol. 1, 168-170.

Ensley, M.R., & Kaber, D.B. (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task, *Ergonomics*, 42, 462-492.

Endsley, M.R., & Kiris, E.O. (1995). The out-of-the-loop performance problem and level of control in automation. *Human Factors*, 37(2), 381-394.

FAA NextGen. (2009, February 10). *FAA's NextGen Implementation Plan.* Washington, DC: Federal Aviation Administration. Retrieved August 31, 2009, from http://www.faa.gov/about/initiatives/nextgen/media/ngip.pdf

FAA Order 7610.4k. (2004). Special military operations. Section 9: Remotely operated aircraft (ROA). In: Airspace Integration Plan for Unmanned Aviation. Washington, DC: Office of the Secretary of Defense.

Farrell S., & Lewandowsky S. (2000). A connectionist model of complacency and adaptive recovery under automation. *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 26, 395-410.

Flach, J. (1998). Uninhabited combat aerial vehicles: Who's driving? In: *Proceedings of the human factors and ergonomics society 42nd annual meeting* (pp 113-117). Chicago, IL.

Galster, S.M., Bolia, R.S., Roe, M.M., & Parasuraman, R. (2001). Effects of automated cueing on decision implementation in a visual search task. In *Proceedings of the human Factors and Ergonomics Society 45th Annual Meeting* (pp. 321-325). Santa Monica, CA: Human Factors and Ergonomics Society.

Gawron, V. (1997). Lessons learned in using situational awareness to evaluate systems. Paper presented at the 2nd Annual Symposium and Exhibition on Situational Awareness in the tactical air environment. Patuxent River, MD.

Gawron, V.J. (1998). Human factors issues in the development, evaluation, and operation of uninhabited aerial vehicles. *AUVSI '98: Proceedings of the Association for Unmanned Vehicle Systems International* (pp. 431-438). Huntsville, AL.

Guidry, M.J., & Wills, G.J. (2004). Future UAV pilots: Are contractors the solution? *Air Force Journal of Logistics, (28)*4, 2-13.

Hart, S.G., & Wickens, C.D. (1990). *Workload assessment and prediction.* In H. R. Booher (Ed.), MANPRINT: An approach to systems integration (pp. 257-296). New York: Van Nostrand Reinhold.

Hart, S. G. & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In: *Human Mental Workload* (P. A. Hancock and N. Meshkati (Eds.)), 139-183. North-Holland: Elsevier Science.

Hottman, S., Gutman, W., & Witt, G. (2000). *Research and validation of requirements for UAV operations in the USA.* Paris, France: UAV 2000.

Hottman S.B., Hanson K.R., & Berry M. (2008). *Review of detect, sense, and avoid technologies for unmanned aircraft systems* (in review). U.S. Department of Transportation: Federal Aviation Administration.

Hottman S. B., & Sortland K. (2006). UAV Operators, Other Airspace Users, and Regulators: Critical Components of an Uninhabited System. In P. H. Cooke N.J., *Human Factors of Remotely Operated Vehicles* (pp. 37-47). New York: Elsevier Jai.

Hughes, T. (2008). Human-automation coordination in multi-UAV control. *AIAA Guidance, Navigation and Control Conference and Exhibit*, Honolulu, HA, AIAA 2008-6315, 18 August 2008.

Hunn B.P. (2005). The Human Challenges of Command and Control with Multiple Unmanned Aerial Vehicles. *Proceedings of the Human Factors and Ergonomics Society 49th Annual Meeting*, 20-24.

Kaber, D.B., & Endsley, M.R. (1997). The combined effect of level of automation and adaptive automation on human performance with complex, dynamic control systems. In: *Proceedings of the 41st annual meeting of the Human Factors and Ergonomics Society* (pp. 205-209). Santa Monica, CA: Human Factors and Ergonomics Society.

Kaber D.B., & Endsley M.R., (2003) The effects of level of automation and adaptive automation on human performance, situation awareness, and workload in a dynamic control task. *Theoretical Issues in Ergonomics Science* (pp. 1-40).

Liu D., Wasson R., & Vencenzi D.A. (2008). Effects of system automation management strategies and multi-mission operator-to-vehicle ration on operator performance in UAV systems. *Journal of Intelligent and Robotic Systems*, 54, 795-810.

Lorenz, B., Di Nocera, F., Rottger, S., & Parasuraman, R. (2002). Automated fault management in a simulated space flight micro-world. *Aviation, Space, and Environmental Medicine*, 73, 886–897.

Machado, R. (n.d.). *Rod Machado's Instrument Pilot's Handbook.* Retrieved September 11, 2009, from http://www.rodmachado.com/Images/IFR-Chapter-3-%28Pg%2024-33%29.pdf

McCarley, J.S., Wickens, C. D. (2004). Human Factors Concerns in UAV Flight. Urbana-Champaign, IL: Institute of Aviation, University of Illinois; 2004. Retrieved 27 August 2009 from http://www.hf.faa.gov/docs/508/docs/uavFY04Planrpt.pdf

McCarley, J.S., & Wickens, C.D. (2005). *Human factors implications of UAVs in the national airspace.* University of Illinois Institute of Aviation Technical Report (AHFD-05-5/FAA-05-1). Savoy, IL: Aviation Human Factors Division.

Metzger, U., & Parasuraman, R. (2005). Automation in future air traffic management: effects of decision aid reliability on controller performance and mental workload. *Human Factors, 47*(1), 35-49.

Moray, N. (1997). *Models of mental models.* In: Sheridan, T.B. and Lunteren van, T., Editors, 1997. Perspectives on the Human Controller, Erlbaum, Hillsdale, CA.

Mouloua, M., Gilson, R., Daskarolis-Kring, E., Kring, J., & Hancock, P. (2001). Ergonomics of UAV/UCAV mission success: Considerations for data link, control, and display issues. *Proceedings of the Human Factors and Ergonomics Society 45th Annual Meeting*, 144-148.

Nakagawa, G., Witt, G., & Hottman, S.B. (2001). *HALE UAV certification and regulatory roadmap.* TAAC Document C020-01.

Nelson W.T., & Bolia R.S. (2006). Remotely Supervisory Control of Uninhabited Combat Air Vehicles from an Airborne Battle Management Command and Control Platform: Human Factor Issues. In P. H. Cooke N.J., *Human Factors of Remotely Operated Vehicles* (pp. 49-58). New York: Elsevier Jai.

Nelson, J.T., Lefebvre, A.T., and Andre, S.T. (2004). Managing multiple uninhibited aerial vehicles: Changes in number of vehicles and types of target symbology. *Proceeding of the 26th Interservice/Industry Training, Simulation, and Education Conference*. Orlando, FL.

Newcome, L. (2004). *Unmanned Aviation: A Brief History of Unmanned Aerial Vehicles.* American Institute of Aeronautics and Astronautics. Reston: VA.

O'hare, D., & Roscoe, S. (1990). *Flightdeck performance: The human factor.* Ames, IA: Iowa State University Press.

Olson, W.A., & Sarter, N.B. (1998). "As long as I'm in control… ": Pilot preferences for and experiences with different approaches to automation management. IEEE. *In Proceedings of the 4th Symposium on Human Interaction with Complex Systems* (pp. 63-72). Los Alamitos, CA.

Olson, W.A., & Sarter, N.B. (2000). Automation Management Strategies: Pilot Preferences and Operational Experiences. *The International Journal of Aviation Psychology, 10*(4), 327-341.

Oron-Gilad, T., Chen, J. Y., & Hancock, P. A. (2006). Remotely Operated Vehicles (ROVs) From the Top-Down and the Bottom-Up. In P. H. Cooke N.J., *Human Factors of Remotely Operated Vehicles* (pp. 37-47). New York: Elsevier Jai.

Parasuraman, R., & Byrne, E.A. (2003). Automation and human performance in aviation. In: M.A. Vidulich & P.S. Tsang (Eds), *Principles and practices of aviation psychology* (pp. 311-356). Mahwah, NJ: Lawrence Erlbaum Associates.

Parasuraman, R., Molloy, R., & Singh, I.L. (1993). Performance consequences of automation-induced complacency. *International Journal of Aviation Psychology*, 3, 1-23.

Parasuraman, R., & Riley, V. (1997). Human and automation: Use, misuse, disuse, abuse. *Human Factors, 39*, 230-253.

Parasuraman, R., Sheridan, T.B., & Wickens, C.D., (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics, 30*(3), 286-297.

Pederson, H.K., Cooke ,N.J., Pringle, H.L., & Connor O. (2006). UAV Human Factors: Operator Perspectives. In P. H. Cooke N.J., *Human Factors of Remotely Operated Vehicles* (pp. 21-33). New York: Elsevier Jai.

Pew, R. (1998). Extracted from Sheridan, (1998). Allocating functions rationally: An ongoing debate about how to divide tasks results in (surprise!) lack of agreement. *Ergonomics in Design*, 20-25.

Pope, A.T., Bogart, E.H., (1992). Identification of hazardous awareness states in monitoring environments. *SAE 1992 Transactions: Journal of Aerospace 1992*; 101:448 –57.

Putzer, H., & Onken, R. (2001). COSA: a generic approach towards a cognitive system architecture. In: The cognitive work process: automation and interaction. *Eighth European Conference on Cognitive Science Applications in Process Control, CSAPC'01*, Munich, Germany, September 2001, 24-26.

Reynolds, C. and Wilson, T. (2008). Regulatory gap analysis: Detect, sense, and avoid technologies for UAS. FAA Technical Report DOT/FAA/(AR)-xx/xx. (Under review.)

Rovira, E., McGarry, K., & Parasuraman, R. (2002). Effects of unreliable automation on decision making in command and control. *Human Factors and Ergonomics Society 46th Annual Meeting* (pp. 428-432). Santa Monica, CA: Human Factors and Ergonomics Society.

Ruff, H.A., Calhoun, C.L., Draper, M.H., Fontejon, J.V., Guilfoos, B.J. (2004). Exploring automation issues in supervisory control of multiple UAVs. *Proceedings of the Second Human Performance, Situation Awareness, and Automation Conference (HPSAA II)*, Daytona Beach, FL, March 22-25.

Ruff, H.A., Narayanan, S., & Draper, M.H. (2002). Human interaction with levels of automation and decision-aid fidelity in the supervisory control of multiple simulated unmanned air vehicles. *Presence, 11*, 335-351.

Sanders, M.S., & McCormick E.J. (1993). *Human Factors in Engineering Design (7th Edition)*, New York, NY: McGraw-Hill.

Sarno, K.J., & Wickens, C.D. (1995). The role of multiple resources in predicting time-sharing efficiency: An evaluation of three workload models in a multiple task setting. *International Journal of Aviation Psychology, 5*(1), 107-130.

Sarter N.B., & Amalberti, R. (2000). *Cognitive engineering in the aviation domain.* Hillsdale, NJ: Erlbaum.

Sarter, N. B., & Woods, D. D. (1997). Teamplay with a powerful and independent agent: A corpus of operational experiences and automation surprises on the airbus A-320. *Human Factors, 39,* 553–569.

Sarter, N.D., Woods, D., & Billings, C. (1997). Automation surprises. In: G. Salvendy (Ed.), *Handbook of human factors and ergonomics* (pp. 1926-1943). New York: Wiley.

SC-203, (2007). Guidance Material for Considerations for Unmanned Aircraft Systems. RTCA, DO-304/SC-203, March 22, 2007.

Scarborough, R. (2003). "Hovering spy plane helps rout Iraqis," *The Washington Times*, April 3, 2003, 1.

Schulte, A. (2002). Cognitive automation for tactical missions management: Concept and prototype evaluation for in flight simulator trials. *Cognition, Technology & Work,* 4, 146-159.

Sheridan, T.B. (1998). Allocating functions rationally between human and machines. *Ergonomics in Design*, 6(3), 20-25.

Sheridan, T.B. (2002). *Humans and automation: System design and research issues.* Hoboken, NJ: Wiley.

Sheridan, T.B., & Verplank, W.L. (1979). *Human and computer control of undersea teleoperators*. Man-Machine Systems Lab Report. Cambridge: Massachusetts Institute of Technology.

Spirkovska, L. (2006). Intelligent Automation Approach for Improving Pilot Situational Awareness. NASA AMES Research Center, Report Number: NASA/TM-2004-212845.

Strater, L.D., Endsley, M.R., Pleban, R.J., & Matthews, M.D. (2001). Measures of platoon leader situation awareness in virtual decision making exercises, Research Report 1770. Alexandria, VA: Army Research Institute.

Teal Group. (2009, February 17). Teal Group Predicts Worldwide UAV Market Will Total Over $62 Billion. Retrieved August 31, 2009, from http://www.tealgroup.com/about-teal/teal-group-in-the-media/3/40-teal-group-predicts-worldwide-uav-market-will-total-over-62-billion-

Thompson, W.T., Lopez, N., Hickey, P., DaLuz, C., Caldwell J.L., Tvaryanas A.P., (2006). Effects of shift work and sustained operations: operator performance in remotely piloted aircraft (OP-REPAIR). Brooks City-Base, TX: United States Air Force, 311th Human Systems Wing. Report No.: HSW-PE-BR-TR-2006–0001.

Tirre, W. (1998). Crew selection for uninhabited air vehicles: preliminary investigation of the air vehicle operator (AVO). *Proceedings of the human factors and ergonomics society 42nd annual meeting* (pp.118-122).

Tso, K.S., Tharp, J.K., Tai, A.T., Draper, M.H., Calhoun, G.L., Ruff, H.A.: A human factors testbed for command and control of unmanned air vehicles. *Digital Avionics Systems 22nd Conference*. Indianapolis, IN.

Tvaryanas AP, Thompson WT, Constable SH., (2006). Human factors in remotely piloted aircraft operations: HFACS analysis of 221 mishaps over 10 years. Aviation Space Environment Med; 77:724–32.

Walter B.E., Knutzon J.S., Sannier A.V., Oliver J.H. (2004). Virtual UAV ground control station. *AIAA 3rd "Unmanned Unlimited" Technical Conference, Workshop, and Exhibit.* Chicago, IL, AIAA 2004-6320, September 20, 2004.

Wasson, R.J., (2005). The Effect of Level of Automation and Operator-to-Vehicle Ratio on Operator Workload and Performance in Future UAV Systems. Unpublished Masters Thesis, Embry-Riddle Aeronautical University, Daytona Beach, FL.

Weeks, J.L. (2000). *Unmanned aerial vehicle operator qualifications.* United States Air Force Research Laboratory, Warfighter Training Research Division, AFRL-HE-AZ-TR-2000-0002.

Wickens, C.D., & Hollands, J., (2000). *Engineering psychology and human performance (3rd ed.).* Upper Saddle River, NJ: Prentice-Hall.

Wickens, C.D., (1992). Engineering psychology and human performance (2nd ed.). Scranton, PA: HarperCollins.

Wiener, E.L. (1988). Cockpit Automation. In E.L. Wiener and D.C. Nagel (Eds). *Human Factors in Aviation* (pp. 433-450). San Diego, CA: Academic Press.

Wiener, E.L. (1989). Human Factors of Advanced Technology ("Glass Cockpit") Transport Aircraft. NASA Contractor Report 177528, NASA Ames Research Center, June 1989.

Wiener, E.L., & Curry, R.E. (1980). Flight deck automation: Promises and problems. *Ergonomics, 23*, 995-1011.

Williams, K.W. (2004). *A summary of unmanned aircraft accident/incident data: Human factors implications.* Technical Report Publication No. DOT/FAA/AM-04/24.

U.S. Department of Transportation, Federal Aviation Administration, Office of Aerospace Medicine, Washington, DC.

Williams, K.W. (2005). Unmanned Aircraft Pilot Medical and Certification Requirements. In: Krebs, W.K., Unmanned Aerial Vehicles Human Factors, FAA-AAR-100, FY-05, Washington, D.C.

Williams, K.W. (2006). Human Factors Implications of Unmanned Aircraft Accidents: Flight-Control Problems. In P. H. Cooke N.J., *Human Factors of Remotely Operated Vehicles* (pp. 105-116). New York: Elsevier Jai.

Williams, K.W. (2007). *An assessment of pilot control interfaces for unmanned aircraft.* Technical Report Publication No. DOT/FAA/AM-07/8. U.S. Department of Transportation, Federal Aviation Administration, Office of Aerospace Medicine, Washington, DC.

Williams, K.W. (2008). *Documentation of sensory information in the operation of unmanned aircraft systems.* Technical Report Publication No. DOT/FAA/AM-08/23. U.S. Department of Transportation, Federal Aviation Administration, Office of Aerospace Medicine, Washington, DC.

Wilson, J. R. (2007). Manned and unmanned aircraft to share controlled and commercial airspace. *Military & Aerospace Electronics, Jan 2007, 18*(1), 24.

Worch, P.R., Borky, J., Gabriel, R., Heiser, W., Swalm, T., & Wong, T. (1996). *United States Air Force Scientific Advisory Board report on UAV technologies and combat operations.* SAB-TR-96-01. Washington, DC: General Printing Office.

Appendices

Appendix A

Unmanned Aircraft System (UAS) Automation and Pilot Selection Study

Conducted by Chris Reynolds
Advisor: Dr. Dahai Liu
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600 S. Clyde Morris Blvd, Daytona Beach, FL 32114

The purpose of this study is to examine the effect of automation styles and learned skill-sets on performance, workload, and situation awareness. This experiment consists of one session that will last approximately one hour. During this session, you will be asked to complete two computer-based UAS simulation trials and fill out questionnaires regarding your perceived feeling of situation awareness and workload.

Your participation in this study will help us determine an appropriate level of automation and help distinguish potential pilot candidates for future UASs. There are no known risks associated with this experiment. The data collected from your participation will remain completely anonymous. You will be compensated for your participation with a $15.00 cash incentive and will be eligible to receive a $50.00 cash prize for best overall performance. You may terminate your participation at any time.

Thank you for your participation. If you have any questions, please ask during the experiment, or call Chris Reynolds at 719.640.7142 or Dr. Dahai Liu at 386.226.6214.

Statement of Consent

I acknowledge that my participation in this experiment is entirely voluntary and that I am free to withdraw at any time. I have been informed as to the general scientific purposes of the experiment and that I will receive $15.00 for completion of this study and will be eligible to receive $50.00 in the event that I have the best overall task performance in the entire study. Both rewards are contingent upon completion.

I acknowledge that I have had the opportunity to obtain additional information regarding the study and that any questions I have raised have been answered to my full satisfaction.

I have read and fully understand the consent form and I sign it freely and voluntarily.

Participant's Name: ___________________________________

Participant's Signature: ________________________________ Date___________

Experimenter Signature:________________________________ Date___________

Appendix B

Biographical Information Questionnaire

Please fill in the blanks or circle the appropriate response.

1. What is your age? ________ years
2. What is your gender? M / F
3. Do you have normal or corrected to 20/20 vision? Yes / No
4. Are you color blind? Yes / No
5. Are you: R-handed / L - handed
6. What is your current learned skill-set? Pilot ATC Other
    a. If Pilot:
        i. What is the highest rating you hold? Private Instrument Commercial
        ii. What is your total PIC time (approx.)? _________ hours
        iii. What is your total Instrument (including simulated) time? ________ hours
        iv. Are you current? Yes / No
        v. How many hours have you flown in the past month (approx.)? _______ hours
    b. If ATC:
        i. Check the courses that you have completed or are currently enrolled in?
        ATM-I ___ ATM-II___ ATM-III___ ATM-IV___ ATM-V___
        VFR Control Tower/AT315___ Non-Radar ATC/AT406__
        ii. How many hours have you spent performing ATC-based duties within the last month: ______ hours
7. How many hours per week do you use computers: _____ hours
8. On a scale of 1 to 5, what is your confidence level in using computers:
    LOW confidence 1 2 3 4 5 HIGH confidence
9. On average, how many hours per week do you spend playing computer games?
    0-5___ 6-10___ 11-15___ 16-20___ 21-25+___
10. What type of genre of gaming are you most accustomed to playing?
    Action___ Adventure___ Role-Playing___ Strategy___ Simulation___
11. Have you had any other experience participating in unmanned aircraft simulation? Yes / No
12. Do you have any experience flying unmanned aircraft or remote controlled aircraft? Yes / No
    a. If so, please explain:
    ____

Appendix C

NASA Task Load Index (TLX) Form (Presented after the completion of each trial)

We are interested in your subjective experience of workload. Workload is a difficult concept to define precisely, but a simple one to understand generally. The factors that influence your experience of workload may come from the task itself, your feelings about your own performance, how much effort you put in, or the stress and frustration you felt.

One way to find out about workload is to ask people to describe the feelings they experienced. Because workload may be caused by many different factors, we would like you to evaluate several of them individually rather than lumping them into a single global evaluation of overall workload. This set of six rating scales was developed for you to use in evaluating your experiences during the test trial.

Please indicate the level of workload you experienced on each of the 6 scales by circling the line at the point which best reflects the level of workload you experienced. The ends of the scales are labeled to indicate very low and very high workload. Points in between those end points represent intermediate values of workload. *Please note that the Performance scale goes from Good on the left to Bad on the right. This order has been confusing for some people.*

EFFORT — How hard did you have to work (mentally and physically) to accomplish your level of performance?

| | | | | | | | | | | | | | | | | | | | |

Low **High**

PERFORMANCE — How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

| | | | | | | | | | | | | | | | | | | | |

Good **Poor**

FRUSTRATION LEVEL — How insecure, discouraged, irritated, stressed, and annoyed versus secure, gratified, content, relaxed, and complacent did you feel during the task?

| | | | | | | | | | | | | | | | | | | | |

Low **High**

TEMPORAL DEMAND — How much time pressure did you feel due to the rate or pace at which the tasks or events occurred? Was the pace slow and leisurely, or rapid and frantic?

| | | | | | | | | | | | | | | | | | | | |

Low **High**

MENTAL DEMAND — How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching)? Was the task easy or demanding, simple or complex, forgiving or exacting ?

| | | | | | | | | | | | | | | | | | | | |

Low **High**

PHYSICAL DEMAND — How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating)? Was the task physically easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

| | | | | | | | | | | | | | | | | | | | |

Low **High**

NASA Task Load Index (TLX) Weighting Form

The forms you filled out included six rating scale factors that can influence workload. We are interested in your assessment of the relative contribution of these factors to your experience of workload.

People vary in their opinion of what contributes to workload. For example, some people feel that mental or temporal demands are the essential aspects of workload regardless of the effort they expended or the performance they achieved. Others feel that if they performed well, the workload must have been low and if they performed poorly, the workload must have been high. Yet others feel that effort or feelings of frustration are the most important factors in workload, and so on.

In addition, the factors that create levels of workload differ depending on the task. For example, some tasks might be difficult because they must be completed very quickly. Others may seem easy or hard because of the intensity of mental or physical effort required. Yet others feel difficult because they cannot be performed well, no matter how much effort is expended.

The evaluation you are about to perform is a technique developed by NASA to assess the relative importance of the six factors that were included in the workload rating scale in determining how much workload ***you*** experienced across all the test trials you just completed.

Below is a list of pairs of rating scale titles (for example Effort vs. Mental demand). For each pair, please circle the item that was more important to ***your*** experience of workload across all the test trials you just completed.

MENTAL DEMAND	VS	PHYSICAL DEMAND
TEMPORAL DEMAND	VS	MENTAL DEMAND
PHYSICAL DEMAND	VS	TEMPORAL DEMAND
EFFORT	VS	PERFORMANCE
PERFORMANCE	VS	FRUSTRATION
TEMPORAL DEMAND	VS	PERFORMANCE
MENTAL DEMAND	VS	PERFORMANCE
PERFORMANCE	VS	PHYSICAL DEMAND
EFFORT	VS	FRUSTRATION
TEMPORAL DEMAND	VS	EFFORT
EFFORT	VS	MENTAL DEMAND
PHYSICAL DEMAND	VS	EFFORT
FRUSTRATION	VS	TEMPORAL DEMAND
MENTAL DEMAND	VS	FRUSTRATION
FRUSTRATION	VS	PHYSICAL DEMAND

Appendix D

Post-Trial Participant Subjective SA Questionnaire (PSAQ)

Name:	Task:	Date:

Note: Definitions are provided for reference on the last page.

1. Please circle the number that best describes **how hard you were working** during this scenario.	Not hard	1	2	3	4	5	Extremely hard

Comments:

2. Please circle the number that best describes **how well you performed** during this scenario.	Extremely poor	1	2	3	4	5	Extremely well

Comments:

3. Please circle the number that best describes **how aware of the evolving situation** you were during the scenario.	Not aware of situation	1	2	3	4	5	Completely aware of situation

Comments:

4. Please circle the number that best describes **how aware of Intruding Aircraft** you were during the scenario.	Not aware of situation	1	2	3	4	5	Completely aware of situation

Comments:

5. Please circle the number that best describes **how aware of the Mission Mode Indicator** you were during the scenario.	Not aware of situation	1	2	3	4	5	Completely aware of situation

Comments:

6. Please circle the number that best describes **how well you perceived the operating** environment of the aircraft(s) in which you were flying.	No mental perception	1	2	3	4	5	Very high mental perception

Comments:

7. Please circle the number that best describes **how well you perceived the future status** of the aircraft(s) in which you were flying.	No mental perception	1	2	3	4	5	Very high mental perception

Comments:

8. Please circle the number that best describes **how well you perceived the interaction** of the aircraft(s) in which you were flying with the surrounding environment.	No mental perception	1	2	3	4	5	Very high mental perception

Comments:

Additional Comments:

PSAQ Definitions

Hard Work:
Refers to the overall amount of effort exerted to complete the mission scenario. This is an overall combination of: mental demand, physical demand, temporal/time demand, performance, effort, frustration, etc.

Performance:
Refers to how quickly and correctly you completed the tasks required of you during the mission scenario.

Awareness:
Refers to your ability to quickly and effectively comprehend what is taking place during specific occurrences in the mission scenario.

Perception:
Refers to how well you could visualize or create a mental picture of the situation in your head.