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Eye tracking metrics for workload estimation in flight deck operations

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EYE TRACKING METRICS FOR WORKLOAD ESTIMATION IN FLIGHT DECK OPERATIONS

by

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A thesis submitted in partial fulfillment of the
requirements for the Master of Science degree
in Industrial Engineering in the Graduate College of
The University of Iowa

July 2009

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CERTIFICATE OF APPROVAL

MASTER'S THESIS

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TABLE OF CONTENTS

LIST OF TABLES v

LIST OF FIGURES vi

LIST OF EQUATIONS ix

CHAPTER 1. INTRODUCTION 1

- Statement of the Problem 1
- Proposed Solution Approach 1
- Contributions 2
  - Practical contribution 2
  - Theoretical contributions 2

CHAPTER 2. BACKGROUND 4

- Review of Technical Literature 4
  - Mechanism of visual search 4
  - Impact of individual differences 6
  - Experience-related differences 6
  - Physical-related differences 7
  - Environment-related differences 8
  - Existing eye tracking metrics, trends and measures 9
  - Analysis and ranking of existing eye tracking metrics 23

CHAPTER 3. 737-800 FLIGHT DECK EYE TRACKING RESEARCH STUDY 25

- Methodology 25
  - Hypothesis 25
  - Apparatus 25
  - Smarteye Eye Tracking System 31
  - Design of Experiment 33
  - Participants 44
  - Independent Variables 45
  - Dependent Variables 46
  - Flight Test Matrix 49
- Flight Test Results 50
  - Visual scanning 50
  - Flight performance 50
- Flight Test Conclusions 51

CHAPTER 4. DATA ANALYSIS AND ALGORITHM DEVELOPMENT 52

Data Set 52
Analysis Methodology 60
Results Conclusion 70

CHAPTER 5. CATS INTEGRATION 71

Cognitive Avionics Tool-Set (CATS) 71
Algorithm Implementation 76
Real-Time Workload Estimation 77
Utility of Algorithm for Real-Time Classification 77
Industry Utilization of Operator State Classification Information 78

CHAPTER 6. FUTURE RESEARCH 79

Further Initiatives to Be Pursued 79

APPENDIX 81

BIBLIOGRAPHY 101

LIST OF TABLES

Table 1. Collected Eye Tracking Metrics 24

Table 2. Subjective Responses 48

Table 3. Eye Tracking Metric List 49

Table 4. Reduced Sample Flight Test Matrix 49

Table 5. IOS Collection Data 54

LIST OF FIGURES

Figure 1. Anatomy of the Human Eye 5

Figure 2. Example of Fixation Map on Standard 737 EFIS PFD 20

Figure 3. Example of Fixation Map on Standard 737 EFIS PFD 2 20

Figure 4. OPL 737-800 Flight Deck 26

Figure 5. PFD EFIS 27

Figure 6. MFD NAV Display 28

Figure 7. 737-800 EICAS 29

Figure 8. 737 MCP Configuration 30

Figure 9. 737 Smarteye Camera and Flasher Setup 33

Figure 10. KORD 9R Approach Flight Plan 34

Figure 11. Pilot Approach and Landing Checklist 35

Figure 12. KORD ILS RWY 9R Approach Plate 36

Figure 13. Landing Visual Conditions at Decision Height 38

Figure 14. Go-Around Visual Condition at Decision Height 38

Figure 15. Bedford Workload Scale 41

Figure 16. SART Assessment Card 43

Figure 17. NASA-TLX Assessment Card 44

Figure 18. Boxplot of Average Bedford Score vs. Land/Go-Around, Condition 55

Figure 19. Average Bedford Workload Score Statistics 56

Figure 20. Boxplot of SART Score vs. Land/Go-Around, Condition 56

Figure 21. SART Score Statistics 57

Figure 22. Boxplot of NASA-TLX Score vs. Land/Go-Around, Condition 57

Figure 23. NASA-TLX Total Statistics ... 58

Figure 24. Average Bedford vs. SART Score Regression ... 59

Figure 25. Average Bedford vs. NASA-TLX Total Regression ... 59

Figure 26. Example Boxplot of ET Metric vs. Workload (Max HDG Fixation Duration vs. Workload) ... 62

Figure 27. Eye Tracking Metric vs. Workload Repeated Measures ANOVA ... 63

Figure 28. Eye Tracking Metrics vs. Workload Regression Model ... 64

Figure 29. Task vs. Workload Repeated Measures ANOVA ... 66

Figure 30. Task + ET Metrics vs. Workload Repeated Measures ANOVA ... 67

Figure 31. Task + ET Metrics vs. Workload Regression ... 69

Figure 32. CATS File Selection Window ... 72

Figure 33. CATS Data Integrity Window ... 73

Figure 34. CATS Data Query Window ... 74

Figure 35. CATS World Viewer Window ... 75

Figure 36. CATS Eye Tracking Histogram Window ... 76

Figure A1. Mean Fixation Duration vs. Workload Boxplot ... 81

Figure A2. Global Fixation Frequency vs. Workload Boxplot ... 82

Figure A3. Mean Saccade Length vs. Workload Boxplot ... 82

Figure A4. Max Saccade Length vs. Workload Boxplot ... 83

Figure A5. Mean Airspeed Fixation Duration vs. Workload Boxplot ... 83

Figure A6. Max Airspeed Fixation Duration vs. Worklaod Boxplot ... 84

Figure A7. Airspeed Fixation Frequency vs. Workload Boxplot ... 84

Figure A8. Mean Altitude Fixation Duration vs. Workload Boxplot ... 85

Figure A9. Max Altitude Fixation Duration vs. Workload Boxplot ... 85

Figure A10. Altitude Fixation Frequency vs. Workload Boxplot ... 86

Figure A11. Mean Heading Fixation Duration vs. Workload Boxplot ... 86

Figure A12. Heading Fixation Frequency vs. Workload Boxplot 87

Figure A13. Mean OTW Fixation Duration vs. Workload Boxplot 87

Figure A14. Max OTW Fixation Duration vs. Workload Boxplot 88

Figure A15. Mean MCP Fixation Duration vs. Workload Boxplot 88

Figure A16. Max MCP Fixation Duration vs. Workload Boxplot 89

Figure A17. MCP Fixation Frequency vs. Workload Boxplot 89

Figure A18. Mean MFD Fixation Duration vs. Workload Boxplot 90

Figure A19. Max MFD Fixation Duration vs. Workload Boxplot 90

Figure A20. MFD Fixation Frequency vs. Workload Boxplot 91

Figure A21. Mean Y StdDev vs. Workload Boxplot 91

Figure A22. Mean X StdDev vs Workload Boxplot 92

Figure A23. NASA-TLX vs. Bedford Regression 92

Figure A24. SART vs. Bedford Regression 93

Figure A25. Global Composite Metric Repeated Measures ANOVA 94

Figure A26. ET Metric vs. Workload Regression 95

Figure A27. ET Metrics vs. Workload Repeated Measures ANOVA 96

Figure A28. Task + ET Metrics vs. Workload Regression 97

Figure A29. Task + ET Metrics vs. Workload Repeated Measures ANOVA 98

Figure A30. Task (including land decision) vs. Workload ANOVA 99

Figure A31. Task (incl. land decision) vs. Workload Repeated Measures ANOVA 100

LIST OF EQUATIONS

Equation 1. Entropy Equation 15
Equation 2. Relative Entropy Equation 16
Equation 3: Scan-path indexing function 22
Equation 4. SART Situational Awareness (SA) Equation 42

CHAPTER 1.

INTRODUCTION

Statement of the Problem

For over a century, eye tracking has helped experimenters determine what an individual views, providing clues to what the subject could be cognitively engaged in. However, questions remain as to what metrics work best in determining subject state and, more specifically, subject workload.

Proposed Solution Approach

The basic metrics within eye tracking, such as saccadic movement, fixations and link analysis provide clear measurable elements that experimenters could use to create a quantitative algorithm that reliably classifies operator workload.

Because eye tracking allows for non-invasive analysis of pilot eye movements, from which a set of metrics can be derived to effectively and reliably characterize workload, this research will generate quantitative algorithms to classify pilot state through eye tracking metrics. Through the use of various eye tracking metrics and measures, a correlation between these components will be regressed against pre-determined workload levels as well as self-reported subjective workload ratings in varying flight deck test scenarios. This will improve existing knowledge of eye tracking in flight deck operations and will provide further advancement in the quest for operator state classification.

Contributions

Practical contribution

Operators in today's aircraft flight decks find themselves in various situations that change their cognitive workload. Research to improve the interaction between the operator and the aircraft interface will benefit by being able to analyze operator state quantitatively as opposed to the historical standard of subjective feedback. This eliminates the subjective bias across subjects and standardizes feedback to provide more accurate analysis of operator state in different testing scenarios in flight deck operations. This research is somewhat flight deck specific due to some of the eye tracking measures being specific to flight deck operations, such as entropy, which is dependent on flight task. However, some of the eye tracking metrics that are used to determine workload are common across interfaces, such as fixation duration and blink rate.

Theoretical contributions

Current avionics are not aware of pilot real-time capabilities and limitations resulting from varying workload levels. There exists the potential in various phases of flight and circumstances for information overload in flight deck operations. Several systems within the flight deck itself, such as the flight management system and tethered autopilot, are very effective at making easy procedures easier and hard operations harder in such circumstances; such is the case when unexpected occurrences happen in flight. When the avionics being unaware of pilot state, it is impossible for the avionics to provide dynamic displays that provide the proper information in the proper context and with appropriate levels of automation for various situations based upon the pilot's current abilities.

The concept of the intelligent flight deck is currently being pursued by the National Aeronautics and Space Administration (NASA), with specific interest in characterizing operator state in flight deck operations. The goal is to use operator workload and overall cognitive state effectively to optimize the flight deck interface.

Eye tracking as a remote unattached sensor providing a non intrusive solution that is fully deployable in future flight decks with minor changes to current setup. NASA's IIFD objective to characterize operator state will be supported by these eye movement behavior based workload algorithms.

CHAPTER 2.

BACKGROUND

Review of Technical Literature

Mechanism of visual search

Basic visual search is comprised of two components: fixations and saccadic movements. A *fixation* is a set of look-points or a series of eye gaze vector data points that is focused on a stationary target in the person's visual field (Applied Science Laboratories, 2007). A fixation is the duration of time for which an individual is visually collecting and interpreting whatever information is available within the foveal range of the eye. When the fixation is made on a point close to the individual, such as on a flight deck, visual angle decreases significantly depending on the distance from the eye. The central 1.5 degrees of visual field have a visual resolution many times greater than that of the peripheral vision (Rao, Zelinsky, Hayhoe, & Ballard, 1997). This region of resolution is the only field in which the eye is capable of interpreting fine resolution information, such as words in a book. Converting the reading information analogy to that of heads down displays on a flight deck, the highest resolution necessary of any eye tracker needs to be at least within two degrees visual angle (Rayner & Bertera, 1979). Various components of eye fixations are the duration, the frequency, and the location in which they are made.

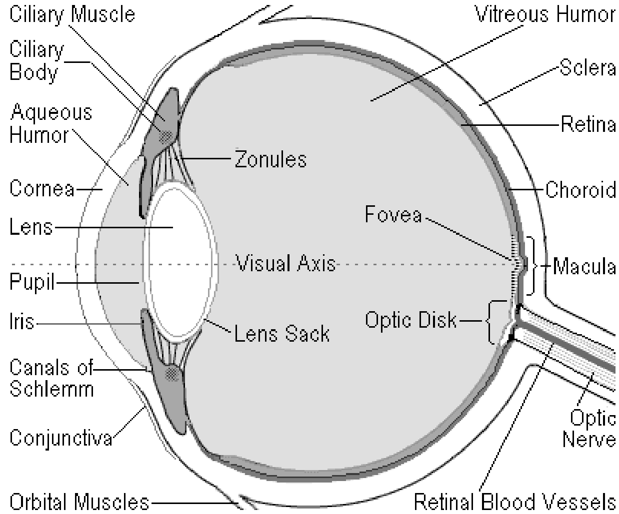


Figure 1. Anatomy of the Human Eye

The eye movement from one fixation to the next is called a *saccade*. A saccade connects one fixation to the next, and can be measured in terms of radial degrees. Different components to a saccade include the length of the saccade (visual angle), the speed of the saccade in degrees per second, and the direction of the saccade. When reading, the eye makes rapid movements, as many as four to five per second, moving from one fixation to the next, focusing on a few words each time (Rayner & Bertera, 1979). The eye does not transmit visual signals to the brain when making a saccade. Therefore, a saccade is made each time information is obtained from one fixation and another fixation is necessary to observe further information elsewhere.

Combining saccadic movements and their associated fixations a *scan pattern* or *scan path* emerges. Since fixations only cover a finite space filled with information, saccadic movements trace the area of desired information so fixations can collect all the information necessary for the brain to interpret the overall image. Previous research provides two suggestions connecting saccadic movements and fixations, concluding on the meaning of scan paths: one proposal indicates that saccadic movements' resulting fixations allow for the formation of visual-motor memory to encode objects and scenes

(Noton & Stark, 1971). Another proposal originating from work done by Yarbus suggests that changes in fixations are most commonly associated with the dynamic demands of a given task (Yarbus, 1967).

Impact of individual differences

There are several components to the differences in eye tracking performance and movement behavior observed across individual subjects: Experience of the subject in performing the given task, physical differences (e.g. Blue versus brown eyes), and environmental condition differences (e.g. vibration). Experience related differences cannot be changed without future manipulation of the pilots themselves through increased training and experience. The easiest target to minimize individual changes is the physical-related differences by simply screening subjects to fit the optimal specifications that work well with the eye tracker.

Experience-related differences

The quality of the eye tracking itself is not affected by differences among pilots' experience, however, the eye tracking metrics themselves can be drastically different. Past research has demonstrated the difference between novice and more experienced participants in various usability studies (Fitts, Jones, & Milton, 1950); (Crosby & Peterson, 1991); (Card, 1984); (Altonen, Hyrskykari, & Raiha, 1998). Common effects are observed in fixation durations, number of fixations, saccadic movements, and scan pattern changes. Experienced pilots will typically be more comfortable while performing a flight task with a basic knowledge of what they need to look at to obtain the information they need. This increases the efficiency of their eye behavior, resulting in a difference in eye tracking metrics in contrast to a novice pilot.

Physical-related differences

Subject's eyes are of paramount concern due to the variance in quality of eye tracking data that can be obtained due to physical differences in the eyes themselves. Subjects with a history of ocular trauma, various ophthalmological diseases (previous or current), lazy eyes, pathologic nystagmus or other ocular disorders, and different forms of corrective lenses including both eyeglasses and contact lenses are likely to cause issues for researchers attempting to obtain consistently high quality eye tracking data. Because of this, it is highly recommended that researchers screen their subjects prior to participation in any eye tracking study to ease the effort required to collect quality eye tracking data from their eye tracker.

Pupil color greatly impacts the quality of eye tracking for many eye trackers. High precision eye trackers require a sharp contrast between the pupil and the iris. Bright pupil systems require direct infrared reflection off of the retina therefore, subjects with blue eyes are often times easier to track. This is due to blue eyes containing less IR-reflective melanin in the iris. In contrast to this, brown or hazel eyes are usually ideal for eye tracking systems that utilize a dark pupil contrast. (Boyce, Ross, Monaco, Hornak, & Xin, 2006); (Wang, Lin, Liu, & Kang, 2005).

Pilots who may be sleep deprived also pose another form of problem. Eyelid closure can become an issue when the eyelid itself begins to cover portions of the pupil. Many remote eye trackers can operate with some part of the pupil being covered, but a majority must still be shown in order for the processing algorithms to calculate the circular center of the pupil that is used as an integral part of gaze vector calculation.

Corrective lenses, such as glasses, pose reflection issues that pose as the biggest threat to eye tracking quality. Lenses posing the largest problem are lenses with hard-edged bi- or tri-focal lenses due to distortion of the eye image as seen from the perspective of the eye tracking cameras. Distortions typically occur due to lens shape, causing problems with systems using corneal reflection, bright retinal reflection, dark pupil circle, limbus or iris features, etc. Soft contact lenses typically do not cause problems however, hard contacts can cause edge problems in bright pupil systems typically caused by dirt or dust trapped beneath the lens. Typically single vision corrective eye glasses do not cause problems unless they have an anti-reflective coating. Lenses with curved front surfaces will often times because of problems caused by reflecting the infrared source back into the camera.

Environment-related differences

There exist several environmental factors that can become problematic to the testing environment incorporating an eye tracker. Many of these issues are observed in dynamic location flight decks, such as that of an actual aircraft flight deck that would experience varying light conditions, turbulence, and other vibration effects that move the pilot' head relative to the eye tracking camera. Since the system is based upon visual contrast, extreme light behaviors pose the greatest threat; usually the only problem in fixed base simulators such as OPL's 737-800 simulator.

Problems associated with extreme ambient light include; too small of pupil diameter, squinting that places the eyelid over the pupil, glare that causes the pilot to change their eye tracking behavior, and degradation of the eye tracker ability to detect features of the face for head tracking purposes. Thankfully, in most simulators the ambient light levels are easily controllable, making it simple to adjust light to be sufficient for normal operations on the flight deck but limiting it enough to optimize eye tracker abilities. This is not as easily controlled in actual flight decks, resulting in other forms of light mitigation that does not impede the pilot's ability to fly under normal conditions.

Existing eye tracking metrics, trends and measures

There exists several different metrics researchers have used over the years to conduct research in the field of eye tracking. One challenge is to identify which metric or combination of metrics is strongly correlated with subjective and objective measures of workload. Depending on the theory of data interpretation, a researcher can infer many things from the eye tracking data set they are analyzing. An eye tracking literature review by Jacob and Karn identified three theories of eye tracking data analysis (Jacob & Karn, 2003):

- Top-down based on cognitive theory: "Longer fixations on a control element in the interface reflect a participant's difficulty interpreting the proper use of that control."
- Top-down based on a design hypothesis: "People will look at a banner advertisement on a web page more frequently if we place it lower on the page."
- Bottom-up: "Participants are taking much longer than anticipated making selection on this screen. We wonder where they are looking."

It is easy to approach a research objective with the top-down cognitive theory in mind. Researchers may have a general idea of how a subject will react, and will look for trends that prove that hypothesis. However, the bottom up approach can lead to new methods of analysis. Post-run analysis can lead to indications of why a subject, in this case a pilot, would spend more time on the attitude indicator than the airspeed indicator, both of which are of high importance. The answers to such questions can lead to further understanding of pilot workload, and what is consuming their cognitive capacity and why.

Initial research in literature review will follow a top-down cognitive theory approach to identifying eye tracking metrics from a simple view of quantifying the raw data collected during this study. Understanding how the research team is attempting to interpret the data is important in determining not only what metrics to use but also how they will be used.

NASA Langley Flight Research has conducted several eye tracking studies in the past resulting in a basic starting platform to compile metrics for many future research initiatives. From this research, a series of basic definitions is utilized to quantify various sets of eye tracking data:

- Average Dwell Time – The total time spent looking at an instrument divided by the total number of individual dwells on that instrument.
- Dwell percentage – Dwell time on a particular instrument as a percent of total scanning time.
- Dwell Time – The time spent looking within the boundary of an instrument.
- Fixation – A series of continuous lookpoints which stay within a pre-defined radius of visual degrees.
- Fixations per dwell – The number of individual fixations during an instrument dwell.
- Glance – A “subconscious” (i.e., non-recallable) verification of information with a duration histogram peaking at 0.1 seconds. (also referred to as an “orphan”)
- Lookpoint – The current coordinates of where the pilot is looking, frequency of data points depending on the eye tracking system used.
- One-way transition – The sum of all transitions from one instrument to another (one direction only) in a specified instrument pair.

- Out of track – A state in which the eye tracking system cannot determine where the pilot is looking, such as during a blink or when the subject's head movement has exceeded the tracking capabilities of the system setup.
- Saccade – The movements of the eye from one fixation to the next. Also considered to be the spatial change in fixations.
- Scan – Eye movement technique used to accomplish a given task. Measures used to quantify a scan include (but are not limited to) transitions, dwell percentages, and average dwell times.
- Transition – The change of a dwell from one instrument to another.
- Transition rate – The number of transitions per second.
- Two-way transition – The sum of all transitions between an instrument pair, regardless of direction of the transition.

(Harris, Glover, & Spady, 1986)

Area of Interest

Areas of interest are regions specified over a field of view that hold significant meaning or indicate a specific source of information. The definition of areas of interest is at the discretion of the researcher. It is critically important to specify what that area of interest represents in order to compile meaningful results. Areas of interest are very task specific, depending on what form of visual scan will be required to complete the task, and what interface is being used (Jacob & Karn, 2003). In flight, regions of interest often include the heads down displays, often broken down into smaller regions including the airspeed indicator, altimeter, attitude indicator, heading indicator, etc.

The limiting factors to the area of interest definition rest solely on the capabilities of the eye tracking system being used. An area of interest can only be as small as the eye tracking system has consistently high performance accuracy of eye gaze vectors. The smaller a region of interest, the more accurate a system must be to identify a person's eye gaze within that region. An area of interest must be specific enough to include the important details of a test platform's field of view, but must not be so specific that no meaningful data is attainable due to the noise of eye tracker inaccuracy.

Fixations

Eye fixations are defined as "a relatively stable eye-in-head position within some threshold of dispersion (~2 deg) over some minimum duration (200ms), and with a velocity threshold of 15-100 degrees per second" (Jacob & Karn, 2003). Several studies have been conducted utilizing eye fixation measures. The total number of fixations has been observed to correlate negatively with efficiency; however, efficiency is seen to correlate negatively with workload (Goldberg & Kotval, 1998).

Total fixations is very dependent on the length of the test run as well, so normalizing it in some fashion to be an applied metric across subjects is necessary. This leads to another metric, *fixation frequency* that shows a positive correlation to subject workload similar to fixation total. Fixation frequency has shown to indicate more effortful search, indicating poor performance accuracy and longer search times in memory tasks (Van Orden, Limbert, Makeig, & Jung, 2001).

Fixation duration, including the mean and maximum duration, indicates increased workload in flight simulator task research. Longer fixations are indicative of increases in cognitive processing loads during a period of time (Callan, 1998). Again, analysis is done using frequency to determine the variance of fixation duration relative to that of the entire data collection. Analysis can be comparative to a single pilot alone or across a pilot population. Factors to consider are the individual differences across pilots' experience and individual scenario situations.

Gaze

Very similar to the fixation metric, gaze analyzes the grouping of fixations within a single region of interest. Much of Fitts' research focused on analysis of the gaze metric, including gaze rate (# of gazes / minute) on each area of interest, gaze duration mean and gaze percentage (proportion of time) in each area of interest for 40 pilots flying an aircraft landing approach (Fitts, Jones, & Milton, 1950). Gaze metrics focus more on the area of interest and what it represents, not only the measure of a fixation in any given region of space.

The gaze metric places meaning behind the location of where a fixation occurs, with the region for which a gaze is calculated can be of any size depending on the area of interest. Measures within the gaze metric include the number of fixations within a single gaze, the total number of gazes, the frequency of gaze and the duration of gaze, including the mean and maximum statistics of this single measure (Hendrickson, 1989).

Saccadic Movement

Measures of saccadic movement are often times neglected in usability research initiatives because many of its close relation to fixations measures, which are easier to examine are used instead. There are several metrics available within the realm of saccadic eye movements that are unique and potentially useful in studies involving task oriented research. The length of the saccade, as well as the speed of which the saccade is made are both very easily calculated measures, simply calculating the distance from one fixation to the next in an ordered pair.

The frequency of longer length saccadic movements could indicate a correlation of decreased efficiency, and potentially an increase in perceived workload. The frequency of specific length saccadic movements requires a limit be set to determine what a longer length saccadic movement is. This is dependent upon the specified areas of interest. Usability research has used the ratio of fixation to saccade times as a measure for analysis (Kotval & Goldberg, 1998). Another method in which to analyze saccadic movement is to simply correlate the average saccadic movement distance over a period of time and track the changes throughout a test run. Further research must be done to validate the inferences associated with the subsets of saccadic movement metrics.

Scan-Path/Link Analysis

Several research studies have been conducted that analyze scan-path as it relates to efficiency, workload, usability, effectiveness, effort, saliency, and other forms of human factors. Scan-path is often looked at as the measurable window that depicts how a subject uses their visual sensory perception to complete any task at hand, carrying with it also the distractions and other important artifacts that are included that add or detract to an individual's intention of completing that task. Scan-path analysis measures the transitions between fixations, including measures of transitions between areas of interest (link-analysis) as a quantifiable measure.

It is particularly useful in bottom-up analysis approaches that seek to identify where someone is looking and why, in an attempt to understand the cognitive background to an individual's eye tracking behavior. Scan-path analysis proves to be critical in computational visual modeling, since hysteresis of scan-path can be observed to identify if a commonality between tasks exists. Scan-path direction was used to determine user behavior in selecting command buttons using varying strategies of selection (Kotval & Goldberg, 1998). Other uses of scan-pattern include reviewing how individuals read over layouts of screen displays (Yamamoto & Kuto, 1992), as well as sweep as an additional scan-path metric indicating a progressive trend in scan-path direction (Altonen, Hyrskykari, & Raiha, 1998).

From a top-down approach scan-path is seemingly less useful. Issues with real time analysis of scan-path as its own metric are that it is difficult to quantify since it is a combination of saccadic movements and fixations in a seemingly random sequence. A scan-path can be used to describe the behavior of an individual's gaze in several areas of interest over time, but only once the scan-path has been made, making it a post process analytical method. Attempts to quantify scan-path have been made by indexing spatial randomness of scan-path behavior relative to what is expected for the given task (Di Nocera, Terenzi, & Camilli, 2006) (see below, *Scan-Path Contrast Indexing).*

Visual Entropy

Other metrics utilizing the idea of scan-paths have been developed by researchers to indicate when a subject's observed scan-path pattern changes. *Entropy* calculates the change observed in an individual's scanning behavior by calculating the standard deviation of fixations (randomness) over a previous period of time and determining the rate of change of that standard deviation in real time. Entropy can be observed by viewing fixation densities over time, particularly useful when done using a fixation map (see below). Entropy as a correlative metric is approach by inferring that as workload increases the observed scan-path becomes less random (Di Nocera, Terenzi, & Camilli, 2006). To contrast this inference, research done by Hilburn suggests that a decrease in mental workload should increase the randomness of the scan-path behavior (Hilburn, 2004).

$$Entropy = H = \sum p_i \log_2 (1/p_i)$$

Equation 1. Entropy Equation

A recent car study utilizes entropy to correlate effectively with a driver's workload by using it as a prediction for where drivers will look depending on the task at hand. By assuming when situations are in high entropy, or high levels of randomness, the probability of looking at everything an equal number of times will transition between all areas of interest and stimuli at near equal frequencies. Each area of interest or fixation point is associated with a state-space probability of subject focus (p_i). The state-space probability changes over time as scan-path trends change, therefore, changing the entropy value (H) (Gilland, 2008).

When focus begins to shift with specific intent due to an induced task or stimuli the attention of the subject is directed to a narrower range of fixation points, thereby decreasing the calculated entropy value. This occurs due to the frequency of other possible fixations and transitions to other areas of interest decreases (lowering the p_i value of a given state-space) since a more systematic pattern of fixations emerges when the subject is in a state of higher focus or higher workload (Gilland, 2008). Important for the use of real-time calculation of entropy if used for workload correlation is *Relative Entropy*. This calculates the entropy relative to the highest value observed for that particular data set or test run.

$$\boxed{RELATIVE\_ENTROPY = H_{observed} / H_{\max}}$$

Equation 2. Relative Entropy Equation

In contrast to the research that provides evidence supporting a low workload – high entropy (increased randomness) correlation, this may not as effectively correlate with tasks on a flight deck. Pilots are heavily trained on proper eye scan techniques for all phases of flight, specifically pilots maintaining an IFR pilot's license. Pilots trained on instrument flight are trained to look at particular instruments in a specific order to ensure that the state of the aircraft is constantly monitored during all phases of flight. With this training eye scan patterns will remain very ordered in constant flight conditions with no change in pilot demands. It may be that eye scan will become more random when demand is increased and a pilot is unable to pay enough attention to their trained eye scan pattern. Entropy changes will still be associated with changes in flight task and workload, but the correlation may not be the same as has been observed in previous research.

Blink Rate

Blink rate has proven to be a metric that correlates with workload regardless of the task variance. Research using air traffic controllers in high and low workload situations suggests that increases in workload negatively correlate with blink rate (Brookings, Wilson, & Swain, 1996); (Wilson, Purvis, Skelly, Fullenkamp, & Davis, 1987). The fundamental belief being that workload is higher requiring more focused attention and a general increase in visual load. Blinks therefore occur less often so it is less likely to miss critical information. This requires the amount of time the eye is collecting information to be increased thereby resulting in a decreased blink rate (Brookings, Wilson, & Swain, 1996).

As an active response to pilot workload correlations, blink rate relative to a baseline average yields the same inverse relationship as shown in a research study done visuospatial memory tasks (Van Orden, Limbert, Makeig, & Jung, 2001). Other research indicates the time between blinks, called interblink interval, positively correlates with workload (Brookings, Wilson, & Swain, 1996). This measure is simply a derivative of the blink rate metric, calculating the time it takes to make a single blink. With an eye tracker that can detect blink rates, blink rate as a metric for analysis proves to be a robust option.

Pupilometry

Pupil changes in dilation and other pupilometry trends have been shown to be instigated by changes in cognitive processing. Pupil diameter has been observed to increase with increased cognitive loading in a color coding and symbolic tactical display study (Backs & Walrath, 1992). Using baseline pupil diameter, the relative changes in diameter were used to correlate with workload levels of subjects identifying several symbols on various displays. Pupil dilation tends to be indicative of increased demand for information processing.

There are two forms of pupil changes; dynamic, such as observed in cognitive processing of discrete sentences (Just & Carpenter, 1993), or sustained pupil changes as seen during digit span recalls (Granholm, Asarnow, Sarkin, & Dykes, 1996). Depending on what type of workload tasks are, the appropriate form of pupillary response is collected. In flight deck operations it is possible for both forms of pupillary responses to be present, as pilots are required to both read information form heads down displays as well as recall information from checklists and radio calls.

With information processing becoming the driver for changes in pupil metrics, it is not task specific and can be applied as a general correlate to workload. The same correlations are likely to apply across testing platforms (i.e. a flight deck or a computer screen). One setback is the demand for high sample rate of pupilometry data from the eye tracker. Due to the speed at which the pupil diameter changes, sample rates upwards of 60 Hz is required to capture sufficient data capable of monitoring significant changes pupil dilation (Just & Carpenter, 1993); (Granholm, Asarnow, Sarkin, & Dykes, 1996).

Fixation Maps

Fixation mapping is the "analysis of eye-movement traces" of a given scene. It is often considered a more complex eye tracking measure as it requires more complex analysis of multiple eye tracking metrics, such as mean fixation duration. A fixation map is used in the quantification of the similarity of traces and the degree of coverage by the fixations of a visual stimulus (Wooding, 2002). By mapping the fixations across a visual scene, such as a flight deck, provides a 2-dimensional record of fixations over a specified time, t_{fm}. The timing variable can be changed to incorporate situation specific analysis or to analyze the entire test run as a whole. It depends on the testing scenario as to how long a fixation map retains its fixation history.

A fixation map is created by giving 2-dimensional coordinates to the fixation itself, and then quantifying it by assigning pixel definition 'd' to that location. The longer and more frequently a given location is fixated upon the greater the value d is. Over time various d values will exist across the fixation map, providing a landscape that describes the eye tracking fixation behavior over a given time t_{fm}.

Figure 2. Example of Fixation Map on Standard 737 EFIS PFD

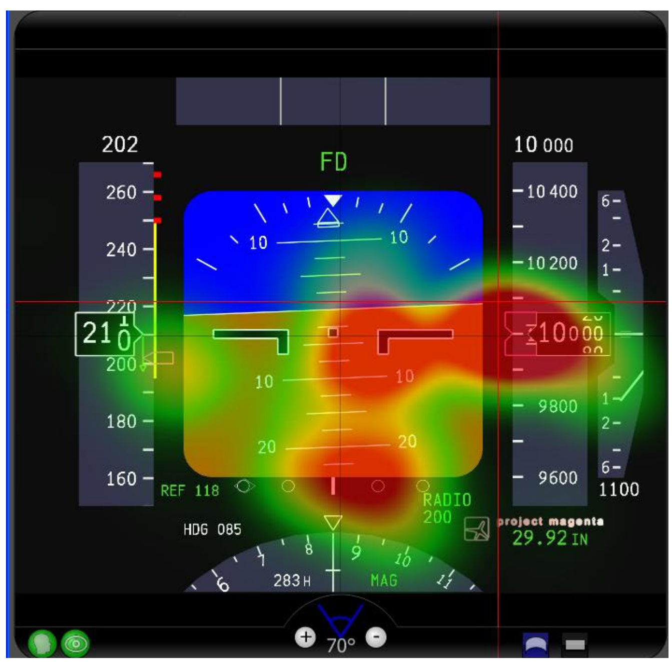


Figure 3. Example of Fixation Map on Standard 737 EFIS PFD 2

Depending on the type of analysis the fixation map 'd' values may be normalized to make comparison across different fixation maps easier. To normalize the fixation map, the greatest value of d is given a value of 1. For analysis to determine if a fixation map contains a greater number of areas of interest (more fixation clusters), normalization is not desirable. To determine areas of interest as specified by the eye tracking fixations a value of d_{crit} may be assigned to a fixation map indicating where areas of interest exist. This value can be shifted to eliminate/create more areas of interest depending on the circumstances of analysis. By increasing d_{crit} there will be fewer areas of interest specified, and in contrast by decreasing d_{crit} there will be more areas of interest.

Analysis to determine visual coverage is done by assigning d_{crit} and then assigning a 1 to all d values greater than d_{crit} and a 0 to all d values less than d_{crit}. The sum of the values of the new binary d values divided by the total number of existing d values (the area of the map) provides the proportion of the map covered by fixations as prescribed by the d_{crit} assignment (Wooding, 2002).

Fixation maps can be further analyzed comparatively by taking the differences of d values and creating a new fixation map of differences. The remainder values indicate where there is contrast between the two fixation maps, larger absolute values indicating larger variance. This is done using normalized fixation maps only so relativity is maintained between the fixation maps.

When analyzing fixation maps it is not the analysis of fixation order, but the location of the fixation that is important. Another method to analyzing fixation maps are done by using standard deviation of fixations from a determined mean location. This is essentially determining the dispersion of fixations across a scene which is scene dependent and not valid for varying flight deck interfaces.

Scan-Path Contrast Indexing

Analysis of scan path is of specific interest to flight deck operations, since there are specific scan paths that are typically taught in flight training of pilots. A scan path is analyzed by first identifying quantitatively the scan-path itself and then contrasting it to that of another scan-path. To determine the differences between scan-paths previous research has used an indexing function that compares scan path frequencies in different situations, often times varying workload, but can be tailored to fit the analysis required.

$$i(s) = (f_{low}(s) - f_{high}(s)) * f(s)$$

Equation 3: Scan-path indexing function

In the index equation; "(s) is defined as one of the used scan-paths of a fixed length, f(s) is the occurrence frequency of the sequence s for the entire scenario, $f_{low}(s)$ is the occurrence frequency for the low difficulty level periods, and $f_{high}(s)$ is the occurrence frequency for the high difficulty level periods" (Simon, Rousseau, & Angue, 1993). As stated earlier, the difficulty designation can be swapped out for scenario differences to create an index contrasting that given scenario. An i(s) index value near zero indicates that the scan-path sequence comparison is not different. To contrast this, when i(s) is negative or positive, the greater the i(s), the more frequent the scan-path s is for the high difficulty scenario.

Simon, Rousseau and Angue's research indicates that when quantifying scan-path as it pertains to workload (difficulty) that there is a greater correlation to ordered scan-paths during lower workloads, and a more random (trigonometric) scan-path at higher workloads. Correlation in subject scan-path index regressed against workload varied from 8% to 20%, which is still a notable for practical purposes of using the scan-path measure. This indicates that workload can be determined from scan-path. However, Simon, Rousseau and Angue argue that this analysis is tedious to perform and is notably more difficult to do automatically as would be desirable.

Analysis and ranking of existing eye tracking metrics

There are several eye tracking metrics that can be chosen from previous research to provide quantitative measures to analyze gaze vector data. The challenge exists in determining what metrics are specific to eye tracking, are general metrics that correlate with workload across tasks, and what metrics are simply of no use. The issue at hand is that visual scanning requirements change frequently as a function of the flight maneuver task (Hankins & Wilson, 1998); (Itoh, Hayashi, Tsukui, & Saito, 1990). Metrics must be chosen either be task specific, or be applicable to all forms of workload scenarios. The other limiting factor is the capabilities of the eye tracker itself. If the collection rate is not fast enough some metrics will not be effective, such as pupilometry measures that require upwards of 60 hertz sample rates.

A compiled list of the core eye tracking metrics has been compiled that are to be used for the research initiatives in estimating workload in flight deck operations. Advanced eye tracking metrics such as entropy and fixation maps are calculated and listed in the data analysis section of this report. Further definition of utilized metrics can be found in the dependent variables section of chapter 3. These metrics were selected for their ability to be utilized not only by themselves, but as composites to more advanced metrics. Fixations and saccadic movements are core metrics due to their being the foundation to the mechanics of eye movement behavior. Statistical subsets of these two metrics are calculated and collected in the data set.

Other metrics include link analysis between the various areas of interest specified on the flight deck (see *dependent variables* section below). Standard deviation of the gaze vector location is calculated in real time based on the previous 30 second period. This metric will provide insight into a form of entropy calculation, determining the rate of change of the standard deviation values. To generalize this measure for each overall test run, the mean X and Y component gaze vector standard deviation is calculated. This metric derived from scan-path randomness (Di Nocera, Terenzi, & Camilli, 2006) and fixation density research (Wooding, 2002) is expected to quantify the change of the existing scan-path pattern and scan-path dispersion.

Table 1. Collected Eye Tracking Metrics

Metric
Fixation Total
Fixation Total for Each Area of Interest
Mean Fixation Duration
Mean Fixation Duration for Each Area of Interest
Max Fixation Duration
Max Fixation Duration for Each Area of Interest
Overall Fixation Frequency
Fixation Frequency for Each Area of Interest
Min Fixation Duration
Min Fixation Duration for Each Area of Interest
Mean Saccade Length
Max Saccade Length
Area of Interest Fixation Percentage
Area of Interest Link Analysis (PFD, MFD, MCP, CDU, MCP, OTW, NONE)
Mean X StdDev
Mean Y StdDev

CHAPTER 3.

737-800 FLIGHT DECK EYE TRACKING RESEARCH STUDY

Methodology

Hypothesis

The flight simulation provides pilots with a complex flight task that will yield a wide variation in relative physical and cognitive workload levels. This will be used to observe pilot's eye movement behavior under these varying conditions. From this it will show that eye movement measures are affected by task loading.

Apparatus

737-800 Flight Simulator

Flight testing was conducted in the Operator Performance Laboratory's 737-800 simulator. The 737-800 simulator is comprised of a fully functional flight deck with full glass cockpit displays, five outside visual projectors, functioning mode control panel (MCP) with autopilot and auto throttle, and standard Boeing 737 controls. The heads down displays (HDD) consist of the left and right seat primary flight displays (PFD), left and right seat multi-function displays (MFD), and the engine indicating and crew alerting system (EICAS) for a total of five heads down displays. The simulator is also equipped with a control display unit (CDU) with fully functional flight management system (FMS).

Figure 4. OPL 737-800 Flight Deck

All HDDs were configured to represent the standard Boeing EFIS display on the PFD. The Boeing EFIS contains several flight critical information gauges within one display as shown in Figure 5. PFD EFIS. This provides the pilot with one display that conveys all current state information, focusing the required scan pattern to a single dense area in contrast to a flight deck with several dispersed gauges.

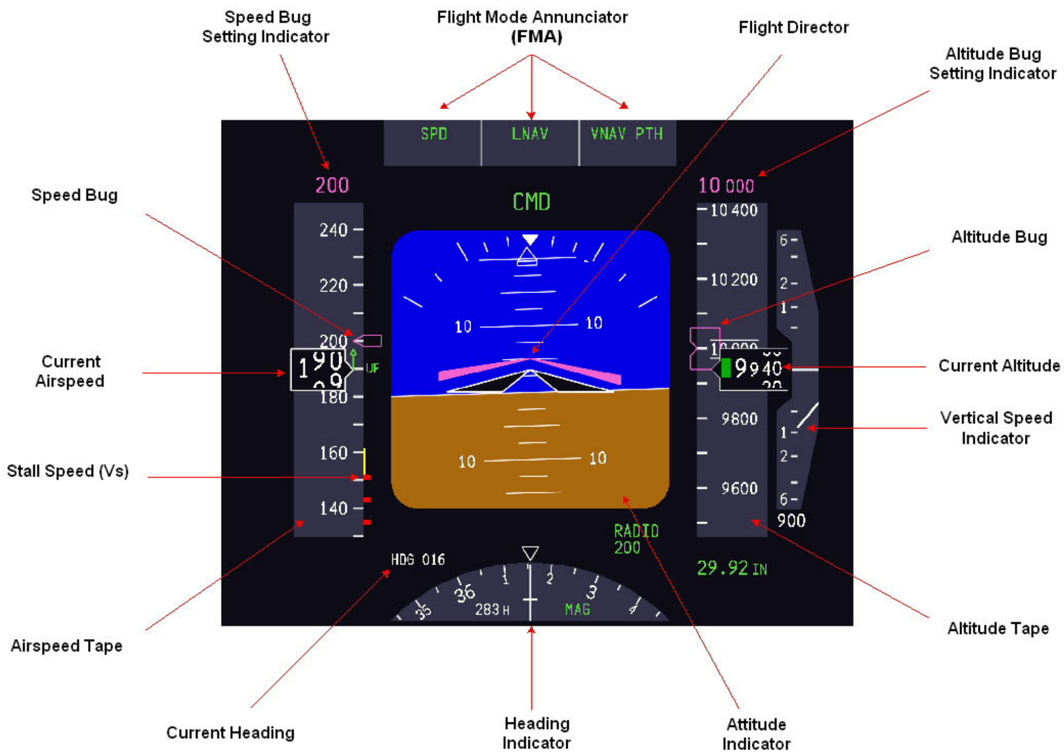


Figure 5. PFD EFIS

The flight mode annunciator indicates the current level of automation controlling the aircraft at any given time. The left box in the FMA indicates the auto throttle control. The middle box in the FMA indicates the horizontal or lateral control automation, and the right box in the FMA indicates the vertical control automation, such as “altitude hold” or “level change”. Other features of the Boeing EFIS are the use of speed and altitude tapes that easily convey the current trend in airspeed and vertical speed of the aircraft. The rate at which the airspeed or altitude tape moves is relative to the acceleration of the direction of travel.

The flight director, utilized in two of the seven test runs indicates the attitude that the aircraft should currently be in to maintain the proper flight path as controlled by either the MCP alone or both the MCP and the flight management system (FMS). The pilot simply controls the aircraft attitude indicator behind the flight director and the proper flight path will be achieved.

Presented on the MFD is a standard navigational display that provides information of aircraft location in relation to navigational waypoints, airports, air stations, and flight path represented by a magenta line as seen in Figure 6. MFD NAV Display The essential value of this display is its ability to show the pilot where they are relative to where they are going, providing both visual and quantitative information. Quantitative information is provided in terms of DME as entered by the navigational frequencies as well as the distance to the next waypoint. Other quantitative information is also presented along the top of the NAV display including true airspeed, ground speed, and current heading. Another feature that is typically found on general aviation aircraft is a turn coordinator, represented on the NAV display as a dotted line projected out from the tip of the ownship symbol that increasingly curls depending on the turn rate of the aircraft.

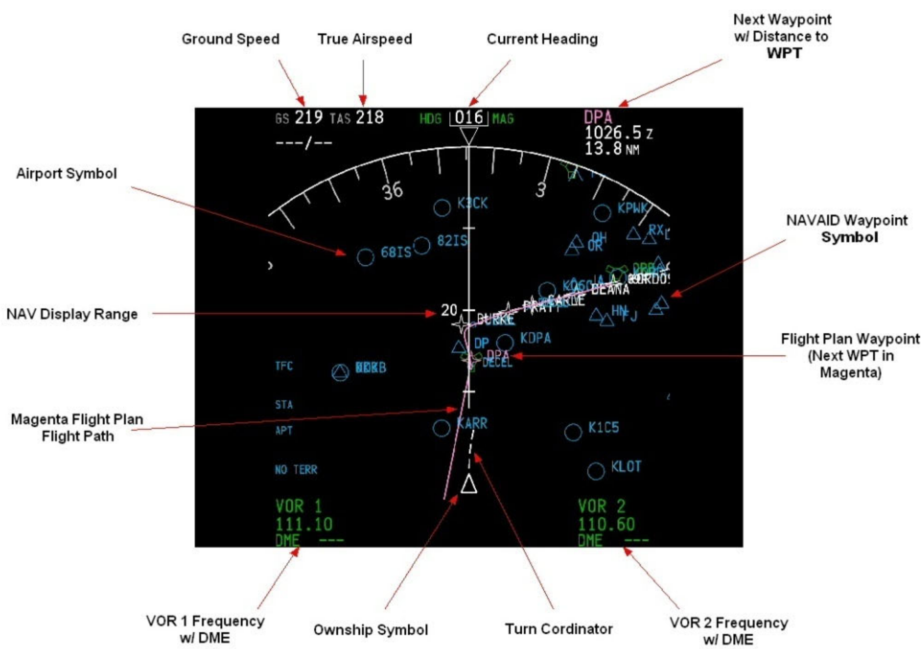


Figure 6. MFD NAV Display

The EICAS is an active state display that indicates engine fan speeds, exhaust gas temperatures, as well as flap and gear settings. In the event of an engine failure, aside from the auditory cue of the engine shutting down, the engine information on the EICAS will show the engine shutting down via decreased fan speed and exhaust gas temperature. This display is also used to present various warnings of any sort to the pilot. However, in the controlled simulation environment of this study the warnings are not utilized.

Figure 7. 737-800 EICAS

The MCP is a primary physical interaction component in this study. Depending on the test run, the level of aircraft flight automation is set on the MCP. There are three specific modes of flight, all of which utilize the MCP in aiding in navigational flight and maintenance of a proper flight path.

In full autopilot flight, the pilot couples the FMS to the autopilot by engaging LNAV and VNAV, for vertical and lateral navigation. To engage the autopilot the CMD button is pressed, and the aircraft is fully coupled to the FMS flight path. Auto throttle is also controlled if it is armed, utilizing the VNAV information from the FMS. When in VNAV/LNAV autopilot mode, the altitude to which the aircraft attempts to maintain is set by dialing the altitude into the MCP as seen in Figure 8. 737 MCP Configuration

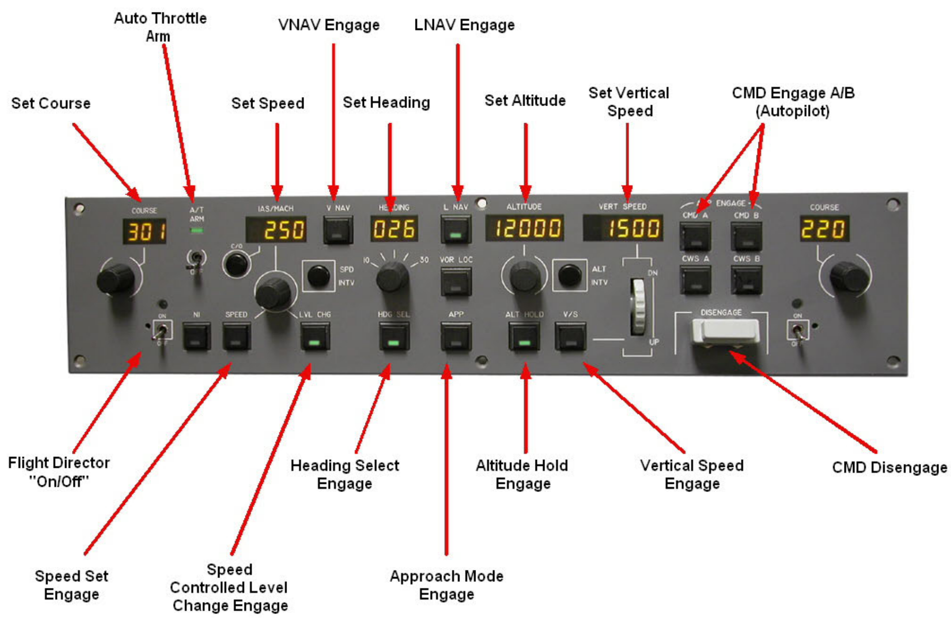


Figure 8. 737 MCP Configuration

For flight director (FD) mode only, the exact same procedure is used when setting the MCP for full autopilot, however, the CMD button is not pressed and the flight director switch is turned to “on”. The flight director can also be used when full autopilot is engaged to provide vectored flight information to the pilot for the purpose of monitoring projected autopilot action. To ensure that autopilot is not engaged during a FD test run, the disengage bar is set effectively ensuring that the CMD is completely uncoupled to the flight controls. The auto-throttle is still engaged as long as the auto-throttle switched is turned on.

When intercepting the localizer on an approach to a runway equipped with a localizer, the pilot switches the aircraft to approach (APP) mode by pressing the approach mode button, changing the source of information that the MCP receives flight path information from. Approach mode uses navigational frequencies set either manually by the pilot or automatically by the FMS. The frequency is designated for a specific runway localizer that the MCP then searches for. The FMA will indicate when the MCP has locked onto the localizer and will then control the aircraft to follow the localizer to the runway regardless of what the heading or altitude is set to. The auto throttle is still controlled by the set speed on the MCP when in approach mode.

For manual flight, no engage buttons are activated on the MCP, including the FD switch turned to off, the auto-throttle arm switch turned off and the disengage bar switched down to the off position. All speed, heading, course, and altitude set indicators can still be manipulated to set the "bugs" on the PFD and MFD. This is useful for pilots to see where the current aircraft state is relative to where it should be as set on the MCP. This is only accurate if the pilot takes the time to set the MCP for the proper speed, altitude and headings appropriately. No other guidance is provided in this mode.

Smarteye Eye Tracking System

To obtain quantitative eye tracking data, a Smarteye eye tracking system was installed and optimized inside the OPL's 737-800 simulator. The Smarteye eye tracker is a remote eye tracking system that uses facial recognition to calculate the position of defined points on a subjects head relative to the calibrated position of 2 or more cameras.

The camera's use the facial features to locate the corners of each of the subject's eyes and digitally zooms to enhance the image of the eye.

To calculate eye gaze vectors from the head origin, infrared led's project infrared light onto the pilots face, illuminating the pilots face as well as creating two ocular reflections; a static corneal reflection and a moving pupil reflection that moves in conjunction with eye movements. By triangulating the angular difference between the corneal reflection and pupil reflection, the Smarteye eye tracking system can create a vector between the two points to create an eye gaze vector originating from the corneal reflection at the center of the subject's eyes.

The 737 flight deck utilized a 3 camera system to achieve the visual angle of eye tracking necessary to capture the test pilots' gaze across the flight deck areas of interest. From the test pilots used in this study, the Smarteye system was optimized to achieve an average overall vector resolution down to approximately 1angular degree, and no greater than 2 angular degrees. From the standard head position of each pilot, a length of about three feet separated most areas of interest from the pilots' eyes, giving an average overall gaze vector resolution of approximately 0.63 inches across the flight deck. This optimization allowed research to be conducted for much smaller areas of interest while retaining consistently accurate and precise eye tracking data.

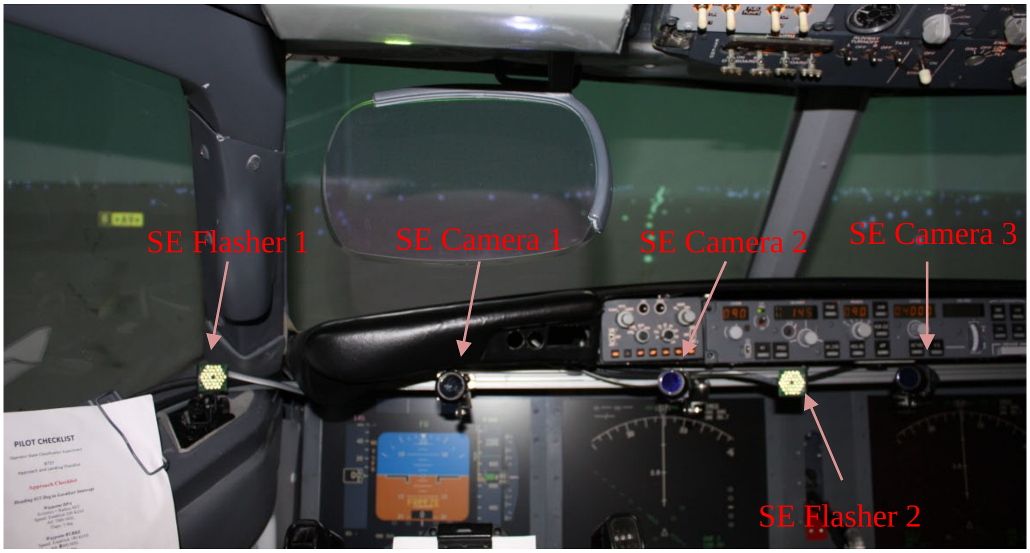


Figure 9. 737 Smarteye Camera and Flasher Setup

Design of Experiment

KORD Runway 9R Approach to Land Task

The main objective to the design of the experiment was to develop a series of flight scenarios that utilized the same flight task but could demand several different levels of workload from the pilot. To accomplish this, a single approach task to Chicago O'Hare International airport was chosen.

The initial point (IP) started the flight test simulation southwest of the DPA VOR at 10,000 feet. Pilots were contacted by Chicago center and instructed to descend to 7000 feet and maintain 200 knots on course to DPA. Approximately 5 NM out from DPA pilots were instructed by Chicago center to contact Chicago approach at radio frequency 119.0. Once contact with Chicago approach was established, pilots were instructed to descend to 6000 feet, continue to waypoint Burke and establish the aircraft on the localizer cleared for runway 9R. Pilots then proceeded to follow the flight plan to waypoints Pratt and Carle. Approximately 1 NM from waypoint Deana pilots were instructed by O'Hare approach to contact O'Hare tower at radio frequency 121.75. With the aircraft inside the outer marker of O'Hare, pilots were cleared to land by the tower. The flight test engineer in the right seat of the flight deck was responsible for making calls to decision height at 1000, 500 and 200 feet to minimums. Upon reaching decision height pilots were expected to make a land or go around call and execute the procedure depending on visual acquisition of the REILs.

The KORD runway 9R approach task includes five waypoints with designated speeds and altitudes pilots were instructed to establish upon reaching that given waypoint:

- DPA – 200 knots at 7000 MSL
- Burke – 180 knots at 6000 MSL
- Pratt – 165 knots at 5000 MSL
- Carle – 165 knots at 4000 MSL
- Deana – 145 knots at 2300 MSL

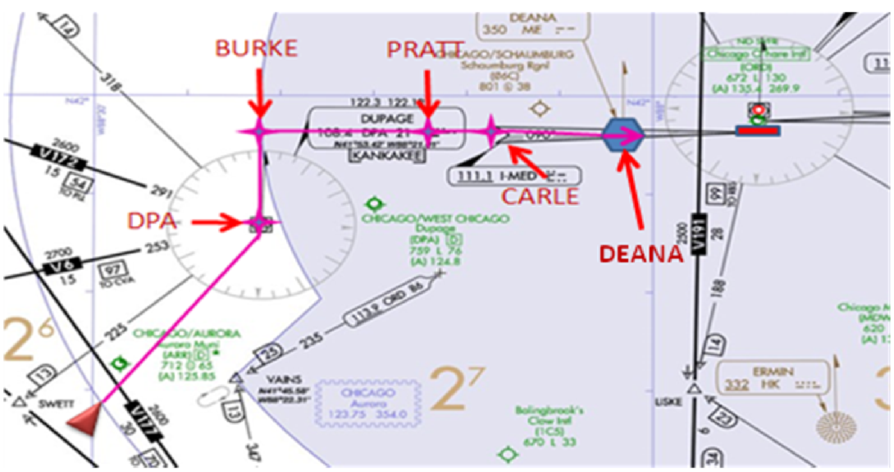


Figure 10. KORD 9R Approach Flight Plan

Pilots were instructed to maintain a sterile cockpit, keeping verbal communication to a minimum during each test run, speaking only during radio calls and workload callbacks. A checklist was provided to the pilots listing each waypoint and the speeds and altitudes they are to establish upon arrival at each waypoint. Also provided for each waypoint were suggested flap positions, MCP engage commands, and gear down instructions.

PILOT CHECKLIST

Operator State Classification Experiment

B737
Approach and Landing Checklist

Approach Checklist

Heading 015 Deg to Localizer Intercept

Waypoint DPA
Avionics + Radios SET
Speed: Establish 200 KIAS
Alt: 7000 MSL
Flaps: 5 deg

Waypoint BURKE
Speed: Establish 180 KIAS
Alt: 6000 MSL
Flaps: 5 deg

Activate MCP APP

Waypoint PRATT
Speed: Establish 165 KIAS
Alt: 5000 MSL
Flaps: 10 deg
Landing Gear DOWN

Waypoint CARLE
Speed: Maintain 165 KIAS
Alt: 4000 MSL
Flaps: 25 Deg

Waypoint DEANA (Localizer Intercept)
Speed: Establish 145 KIAS
Alt: 2300 MSL
Flaps: 30 deg

Landing Checklist

Landing Gear CHECK DOWN
Landing Speed 135 KIAS

Figure 11. Pilot Approach and Landing Checklist

The KORD ILS runway 9R approach plate was also provided to the pilots as a standard in flight reference of the approach task. The ILS approach plates give information to pilots in a familiar form to pilots with an IFR and above license. It lists the typical clearance altitudes to be expected and distances between approach waypoints, as well as radio frequencies of O'Hare approach and O'Hare towers. This information could be used by the pilot to pre-program the radios if so desired to make the flight tasks easier when asked to transfer radio contact to approach or tower. The approach plate was available for all test runs and was the basis for programming the flight plan into the FMS.

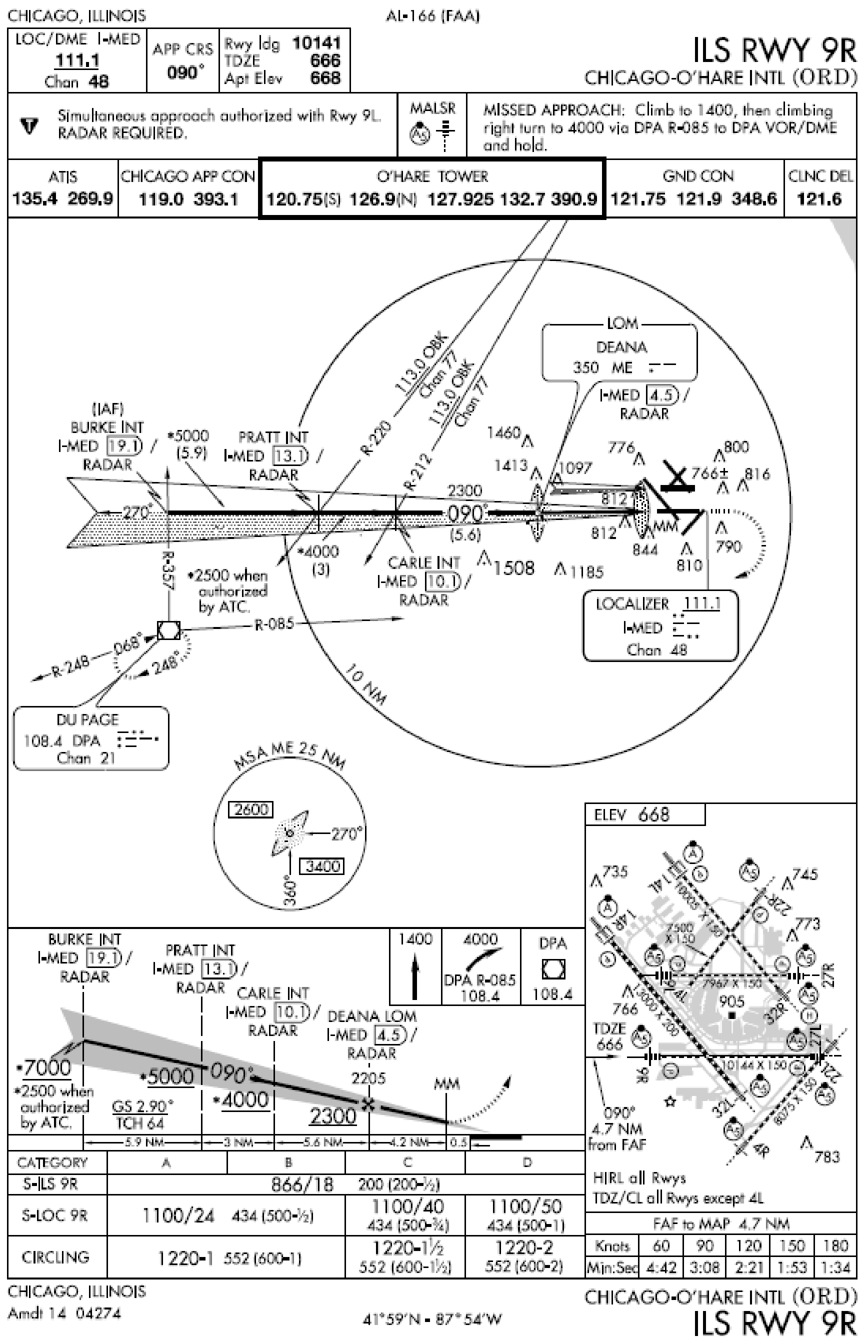


Figure 12. KORD ILS RWY 9R Approach Plate

Test Conditions

Two methods to drive workload to show high-low workload contrasts were implemented:

- Visibility condition – CAT II and CAT III
    - Land or Go Around condition
- Level of automation
    - Full Autopilot and Auto-throttle
    - FD guidance and Auto-throttle
    - Manual approach with localizer course and glide slope guidance only

For the visibility condition, outside visuals were controlled to be set to CAT II visibility, with no greater than 0.3 NM visibility, or set to CAT III, with no greater than 0.1 NM visibility. The threshold of visibility between the two visibility conditions forced the pilot to make a land-no land decision at decision height at 200 feet AGL. Upon reaching 200 feet AGL, federal air regulations (FARs) state that the pilot must be able to see the runway end indicator lights (REILs) to continue to land. If the pilot cannot see the REILs at 200 feet above the runway, the pilot must execute a go-around. If the pilot is able to see the REILs at 200 feet AGL, then the pilot was to proceed to 100 feet AGL where they are required by FARs to make visual contact with the end of the runway to continue to land. The variance in visibility conditions made no impact on the 100 foot AGL decision height. The difficulty for the pilot is found in the time for which the decision to land must be made and to maintain the proper flight path to the runway with no outside visuals obtaining guidance strictly from the HDDs.

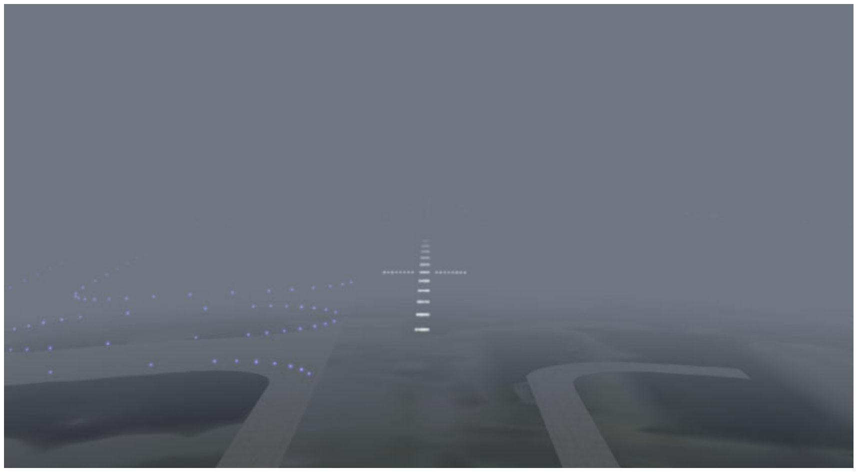


Figure 13. Landing Visual Conditions at Decision Height

Figure 14. Go-Around Visual Condition at Decision Height

The level of automation changed the level of effort that was required of the pilot. For the full autopilot condition, the pilot was simply required to monitor the position of the aircraft, set gear and flaps, and to set the MCP correctly at the appropriate times. The MCP controlled both the yoke and the throttle, allowing the pilot to simply monitor the aircraft state. This condition was designed to impose the least amount of workload on the pilots, since nearly all active control was handled by the MCP and FMS.

The FD guidance condition required the pilot to consistently watch the FD and to manually control the aircraft to follow the cue along the appropriate flight path. In this condition, the auto-throttle was still active, so the pilot was not required to manipulate the throttles to maintain speed, effectively limiting the full potential of high workload imposed on the pilot in the flight deck. The pilot was still required to set the MCP appropriately in the guidance condition.

The manual condition imposed the greatest amount of workload on the pilot by providing no automation on the flight deck. The pilot was responsible for controlling the yoke and the throttle of the aircraft to maintain the proper flight path and speed. The pilot was allowed to use the MCP to provide speed and altitude bugs that assist in reminding the pilot of the speed and altitude they should be maintaining at that current leg of the flight plan. The only guidance available was from the navigational radio tuned to the localizer and the flight plan displayed on the NAV display on the MFD. The localizer, once intercepted, provides course and glide-slope deviation leading up to the end of the runway.

An additional random event engine failure was included to test a pilot’s response to an emergency type situation. The engine failure occurred in the right engine on the final approach in the same location for each pilot. The random event test run was setup with full autopilot and auto-throttle with landing CAT II visibility. The situation was recoverable, but required pilot intervention to maintain the appropriate flight path down to the runway, given the pilot recognized the engine failure in time to recover the aircraft safely.

These two workload drivers of land/go around and automation condition were combined in an experimental matrix (that yielded varying degrees of pilot workload. To add to the pilot workload each test run regardless of workload driver conditions required the pilot to make and receive radio calls as they would in an actual approach to O’Hare.

The pilot was given clearance to waypoints at specific altitudes and speeds. The pilot was also instructed to change radio frequencies when told to switch from Chicago center to O'Hare approach, and again from O'Hare approach to O'Hare tower. Pilots were instructed to read back their instructions as they would typically in standard flight.

A complex hold call was given to pilots on one of the seven test runs. Instructions were given to the pilot not to execute the hold, but to retain the call in memory for 30 seconds and to read them back at the end of the 30 second memory period. This was intended to further increase pilot workload by distracting them cognitively. Correct or incorrect response information was collected by the flight test engineers. The hold call was presented in random order between the various test pilots.

Subjective Workload Assessment

To assess pilot workload, three subjective scales were utilized for each test run; A Bedford workload scale, SART, a situational awareness assessment analysis questionnaire, and the NASA-TLX subject demand assessment. The subjective workload assessment scores provide the baseline connection between the quantitative data results and the pilot's perceived workload for each test run condition. The quantitative data results from the eye tracking metrics will be analyzed and regressed against the pilots subjective workload assessments.

The Bedford workload scale is a 1-10 workload rating assessing the current workload perceived by the pilot. The scale is a decision tree that attempts to minimize the workload reporting differences across pilots. A pilot answers a series of questions to eventually come to a concluding Bedford workload rating as seen in Figure 15. Bedford Workload Scale Workload ratings of 1 through 3 are scores of satisfactory perceived workload. Ratings of 4 through 6 indicate a perceived workload that was tolerable to complete the task, however, could be reasonably reduced. Ratings of 7 through 9 indicate a perceived workload that is not tolerable for the given task, where the pilot feels it is questionable whether or not the task can be completed unless the workload is reduced. A workload rating of 10 is reserved for when the pilot has deemed the workload to be too high to complete the task at all with all available effort exerted to the given task.

Pilots were instructed to memorize the various workload level definitions to prepare them to provide workload ratings mid-flight during each test run. Pilots were asked to respond with a current workload upon starting each test run, and again upon passing each subsequent waypoint, with the last pilot reported score given after passing the last waypoint before landing.

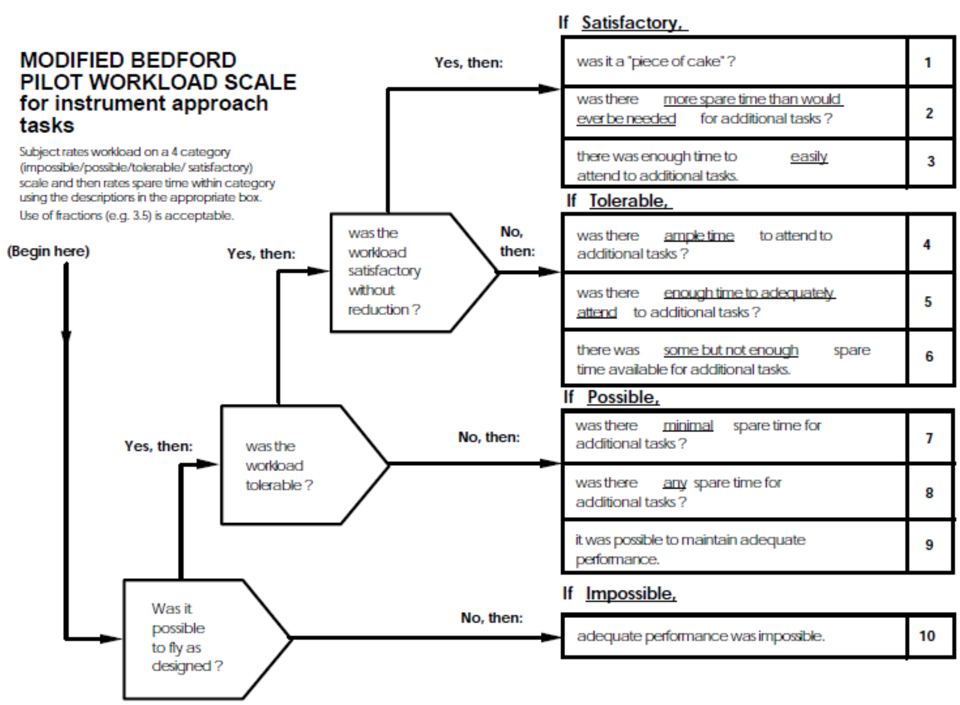


Figure 15. Bedford Workload Scale

The SART assessment was administered after each test run. It assesses the pilot's situational awareness during the entire run by determining the demand on the pilot's attention, the supply of the pilot's attention, and understanding of the attentional resources provided to the pilot. The overall demand is determined by ranking the instability, the variability and the complexity of the given flight task in its specific configuration. Supply of the attentional resources is calculated with four components; arousal, or how stimulated the pilot was during the run, the ability of the pilot to concentrate on the given task, the availability of spare mental capacity, and the capability of the pilot to divide attention. Understanding is a combination of three components of information quality, quantity, and familiarity. All components are rated on a 0 to 7 scale, 0 being a low score and 7 being the high score. The overall SART score is calculated by summing the understanding (U) components, and subtracting the difference of the sums of the demand (D) and supply (S), resulting in Equation 4. SART Situational Awareness (SA) Equation

$$\boxed{SA = U - (D - S)}$$

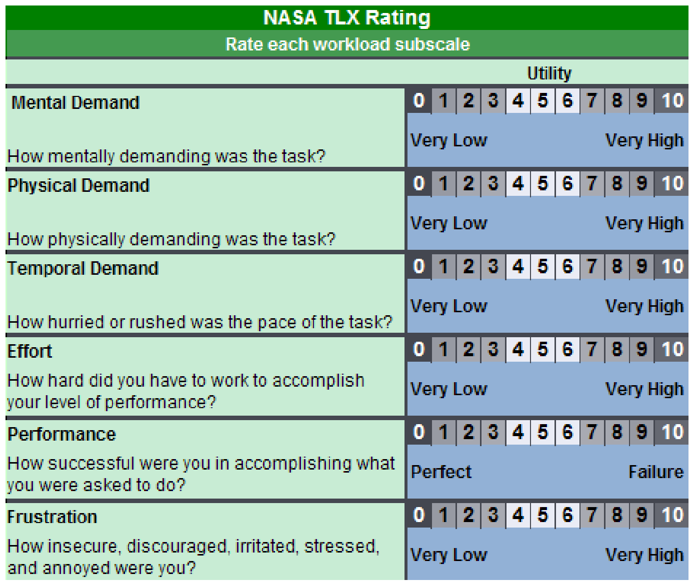
Equation 4. SART Situational Awareness (SA) Equation

Overall, the SART assessment determines the pilot's understanding of what was happening during the test run and their intuitive and experience related response to the condition and information presented to them.

OSCAF In Flight Debriefing Card		
1. Situational Awareness Assessment - SART SA = U - (D - S) Rate each workload subscale		
DEMAND ON ATTENTIONAL RESOURCES (D)	**Instability of Situation** How changeable were the situations and environmental factors encountered in this run?	0 1 2 3 4 5 6 7 Low High
	Variability of Situation Were many elements changing at any one time with large number of dynamic variables?	0 1 2 3 4 5 6 7 Low High
	Complexity of Situation How complicated were the situations in this run ?	0 1 2 3 4 5 6 7 Low High
SUPPLY OF ATTENTIONAL RESOURCES (S)	**Arousal** What was the level of stimulation in this run?	0 1 2 3 4 5 6 7 Low High
	Concentration How much could you concentrate your attention on the important tasks?	0 1 2 3 4 5 6 7 Low High
	Spare Mental Capacity How much mental capacity did you have to spare in this run?	0 1 2 3 4 5 6 7 Low High
	Division of Attention Were you able to divide your attention between several relevant sources?	0 1 2 3 4 5 6 7 Low High
UNDERSTANDING (U)	**Information Quality** How good was the information you obtained in this run?	0 1 2 3 4 5 6 7 Low High
	Information Quantity How much useful information were you able to obtain from all available sources in this run?	0 1 2 3 4 5 6 7 Low High
	Familiarity How familiar were you with the different elements and events in this run?	0 1 2 3 4 5 6 7 Low High

Figure 16. SART Assessment Card

The NASA-TLX assessment, like the SART assessment, was administered after each test run. It is effective in assessing the pilot's perception of their own physical and mental demands during each given test run. Also assessed is the pilot's own perception of their performance. Self assessment questions include; Mental demand, physical demand, temporal demand assessing the speed that was demanded during the task, the level of effort exerted during the task, the pilot's level of performance in accomplishing the task, and the frustration experienced during the task. The scores were based on a 0 to 10 rating scale, with 0 being very low and ten being very high for all assessments in the NASA-TLX except for performance. Performance was rated on the scale of 0 to 10, with 0 being a perfect performance and ten being failure. Upon summing the workload subscale assessments to one combined score results in reporting an overall workload rating with lower scores indicating lower workload and higher scores indicating higher workload.



NASA TLX Rating	
Rate each workload subscale	
	Utility
Mental Demand How mentally demanding was the task?	0 1 2 3 4 5 6 7 8 9 10 Very Low — Very High
Physical Demand How physically demanding was the task?	0 1 2 3 4 5 6 7 8 9 10 Very Low — Very High
Temporal Demand How hurried or rushed was the pace of the task?	0 1 2 3 4 5 6 7 8 9 10 Very Low — Very High
Effort How hard did you have to work to accomplish your level of performance?	0 1 2 3 4 5 6 7 8 9 10 Very Low — Very High
Performance How successful were you in accomplishing what you were asked to do?	0 1 2 3 4 5 6 7 8 9 10 Perfect — Failure
Frustration How insecure, discouraged, irritated, stressed, and annoyed were you?	0 1 2 3 4 5 6 7 8 9 10 Very Low — Very High

Figure 17. NASA-TLX Assessment Card

Participants

Test pilots were chosen based on the criteria of having a current instrument rating or higher. Pilots were further selectively chosen depending on the ability of the Smarteye eye tracking system being able to track their gaze vectors to an acceptable resolution level of 2 degrees of visual angle. This typically required pilots who did not require glasses, or if they did, have corrective lenses that minimized the infrared reflection back into the camera. Qualified pilots requiring corrective lenses were tested on the eye tracking system prior to being considered as test pilots.

The subject pool consisted of twelve (12) pilots, all male, ranging in age from 24 to 60+ with all levels experience in IFR conditions. Participants were instructed to review internal review board (IRB) approval for human subjects testing for this project. Subjects were compensated $20/hour for their time, with a subject testing session typically lasting no longer than four hours.

After signing the IRB form, pilots went through a pre-flight briefing instructing them on the flight task, the automation condition variations, subjective reporting, and the physiological recording equipment that would collect their physiological response to the expected induced workloads experienced in each test run. Pilots were then outfit with the physiological sensors, brought to the flight simulator and a head model built in Smarteye while the pilot was familiarized with the flight model and trained on the standard MCP procedures. After the eye tracking model was validated and established in terms of comfort in using the systems on the flight deck, the pilot was ready to proceed with the flight test.

Independent Variables

The two independent variables as stated above are the level of automation condition and the land or go around visual condition. The automation condition was reduced further into two independent variables, indicating flight director "on" or "off", and autopilot "on" or "off". The independent variables were presented to each pilot in random order, always including a combination of each condition and each land or go-around decision. Simply the order to which the pilot experienced each combination was randomized to reduce the effect of the pilot’s learning curve with increased experience to the flight test.

Dependent Variables

In contrast to the number of independent variables, there are several dependent variables compiled by both the literature review of eye tracking metrics and the reported subjective workload ratings. The eye tracking metrics are all subsets of saccadic movements and fixation durations. Calculated across the flight deck and within specific regions of interest there are several metrics calculated over each entire run; the total number of fixations, the mean fixation duration, the max fixation duration, the fixation frequency, and for the specific regions of interest, the fixation percentage relative to the total number of fixations. Saccadic metrics include mean and max saccade length across the flight deck, and mean and max saccade length coming into and leaving each area of interest.

Areas of interest include; the flight mode annunciator (FMA), the attitude indicator (AI), the airspeed indicator (ASI), the altitude display, the heading display, the multi-function display (MFD), and the mode control panel (MCP). Other metrics collected are the mean X and Y gaze vector component standard deviations. The standard deviation of the gaze vector is calculated over a thirty (30) second period and outputs a value relative to the average gaze vector location. This effectively assesses the spread of the data over the previous thirty seconds. The average value of these averages generically indicates the spread of the scan pattern over the entire test run.

Link analysis is also recorded, counting the total number of links between regions of interest. A link is defined for this experiment as a fixation made in one region of interest followed by a single saccade to another fixation within another region of interest.

Link analysis is calculated as a one-way transition, meaning a count between the MFD to the PFD is a separate count than that of the PFD to the MFD. Link analysis is calculated for the following areas of interest:

- MFD
- PFD
- MCP
- OTW
- NONE

The area of interest ‘none’ is a combination of gaze vectors that do no intersect areas of interest in the defined world coordinate model defined in the Smarteye software. This does not include times when the gaze vector was not calculated, but only when a previous fixation was made somewhere outside the areas of interest, such as out the window or a gaze toward the pilot checklist.

Table 2. Subjective Responses

Metric Type	Metric
BEDFORD	**IP - DPA**
BEDFORD	**DPA-BURKE**
BEDFORD	**BURKE-PRATT**
BEDFORD	**PRATT-CARLE**
BEDFORD	**CARLE-DEANA**
BEDFORD	**DEANA-MINIMUMS**
BEDFORD	**AVERAGE BEDFORD**
SART	**Instability**
SART	**Variability**
SART	**Complexity**
SART	**Arousal**
SART	**Concentration**
SART	**Spare Mental Capacity**
SART	**Division of Attention**
SART	**Information Quality**
SART	**Information Quantity**
SART	**Familiarity**
SART	**SART SCORE**
NASA-TLX	**Mental Demand**
NASA-TLX	**Physical Demand**
NASA-TLX	**Temporal Demand**
NASA-TLX	**Effort**
NASA-TLX	**Performance**
NASA-TLX	**Frustration**
NASA-TLX	**NASA-TLX Total**

Table 3. Eye Tracking Metric List

Metric Type	Metric	Metric Type	Metric	Metric Ty	Metric
ET	Fixation Total	ET	Heading Fixation	ET	CDU Fixation
ET	Mean Fixation	ET	Heading Fixation	ET	CDU Fixation
ET	Max Fixation Duration	ET	FMA Fixation Total	ET	MCP Fixation Total
ET	Fixation Frequency	ET	Mean FMA Fixation	ET	Mean MCP Fixation
ET	Min Fixation Duration	ET	Max FMA Fixation	ET	Max MCP Fixation
ET	Mean Saccade Length	ET	FMA Fixation	ET	MCP Fixation
ET	Max Saccade Length	ET	FMA Fixation	ET	MCP Fixation
ET	Airspeed Fixation	ET	AI Fixation Total	ET	Mean X StdDev
ET	Mean Airspeed	ET	Mean AI Fixation	ET	Mean Y StdDev
ET	Max Airspeed Fixation	ET	Max AI Fixation	ET	Link Analysis Entropy
ET	Airspeed Fixation	ET	AI Fixation Frequency	ET	MFD - PFD
ET	Airspeed Fixation	ET	AI Fixation Percentage	ET	PFD - Left MFD
ET	Altitude Fixation Total	ET	MFD Fixation Total	ET	Left PFD - MCP
ET	Mean Altitude	ET	Mean MFD Fixation	ET	MCP - Left PFD
ET	Max Altitude Fixation	ET	Max MFD Fixation	ET	Left MFD - MCP
ET	Altitude Fixation	ET	MFD Fixation	ET	MCP - Left MFD
ET	Altitude Fixation	ET	MFD Fixation	ET	None - Left PFD
ET	Heading Fixation Total	ET	CDU Fixation Total	ET	Left PFD - None
ET	Mean Heading	ET	Mean CDU Fixation	ET	None - Left MFD
ET	Max Heading Fixation	ET	Max CDU Fixation	ET	Left MFD - None
		ET	None - MCP		
		ET	MCP - None		

Flight Test Matrix

Table 4. Reduced Sample Flight Test Matrix

Run	Condition	Land or Go Around	Eye Tracking Metric 1	Eye Tracking Metric 2	Eye Tracking Metric XX	Bedford Workload	SART Score	NASA TLX
1	Full Auto	LAND	**	**	**	**	**	**
2	Guidance	LAND	**	**	**	**	**	**
3	Manual	LAND	**	**	**	**	**	**
4	Full Auto	GO AROUND	**	**	**	**	**	**
5	Guidance	GO AROUND	**	**	**	**	**	**
6	Manual	GO AROUND	**	**	**	**	**	**
7	Full Auto	Engine Failure	**	**	**	**	**	**

Flight Test Results

Visual scanning

Upon visual inspection of eye tracking results during flight test runs, pilots' eye movements varied drastically between the various flight conditions they were subjected to. Many of these differences are likely due to the different test condition requiring a different scan path to complete the task at hand. The variance in flight test conditions, such as level of automation, is a task that requires the pilots to more frequently monitor the PFD in manual flight conditions to maintain safe flight relative to that of the fully automated condition. Eye tracking metrics that are directly associated to workload will emerge in the eye tracking data regardless of task variance. Other metrics require the assumption that a specific flight task demands a specific form of eye movement tendencies, and that a workload can be correlated to those specific tendencies which reflects the difficulty of the flight task. Review of the eye tracking data set from this flight test is an attempt to identify which metrics effectively correlate to pilot workload driven by each flight condition presented.

Flight performance

Under the automated condition pilots were required to press buttons at specific times and make the standard radio calls. Flight performance was very standardized across pilots in the full automation condition. As expected from the design of the experiment flight tasks, the guidance condition with auto-throttle required moderate interaction from the pilots, yielding some varying results across the test group. Some pilots who had experience utilizing a flight director performed the flight tasks with greater ease than those pilots experiencing it for the first time that day. This experience related difference yielded varying subjective workload feedback from the pilots. The highest reported workloads did come from the manual flight test condition, when pilots were required to control both the attitude of the aircraft and the speed, requiring the most mental cognition from the pilot to maintain the specified aircraft state at the right times and locations.

Several times pilots would find themselves off-course due to the high mental demand required by several systems at once, such as thrust level, attitude adjustment and radio communication. Diverging oscillations in recovering the flight path intercept was very typical across pilots in the manual condition, ultimately driving the pilots' workload to higher levels on the Bedford workload scale.

Flight Test Conclusions

The flight test was run as expected with no changes necessary from the first pilot to the last. Like any other experiment, system malfunctions imposed minor setbacks in timing during some of the runs, however, did not affect the data in any significant way. Pilot responses indicated significant workload variance upon initial inspection of subjective results and verbal pilot feedback. Collected data integrity was actively monitored during all flight test runs.

CHAPTER 4.

DATA ANALYSIS AND ALGORITHM DEVELOPMENT

Data Set

The data was collected and stored on removable drives on the input/output system (IOS) computer connected to the flight simulator. Several systems were connected to the data collection IOS that were used for physiological assessment as well as the simulator command components mentioned in chapter 3. Several buses collected several variables useful in the data analysis of this study, as well as other studies with an interest in operator state classification, shown in Table 5. IOS Collection Data.

Data collection included several components not pertinent to eye tracking, but overall operator state through several channels of physiological output of the subject. The IOS included a 'Stamp' to separate out each data point by frame number and by time, 'Run Info' to record which data set belonged to which subject and task that each subject was performing, aircraft state information, instrumentation recording pilot control inputs, nexus physiological measurement data, recording ECG for heart-rate, respiration rate and depth, EMG collecting right arm deltoid flexion to collect MCP button presses and throttle manipulation, and the eye tracking output information from the Smarteye system described in greater detail in the *Smarteye Eye Tracking System* section of chapter 3.

The quality of the data set is very robust for all eye tracking metrics analyzed across the entire flight deck. However, pre-processing software output did not provide consistent data for all aforementioned regions of interest. Altitude, heading, MFD, speed, out the window (OTW), and MCP regions were captured and entered into the data set. Attitude indicator and FMA were not collected due to errors in region labeling during data collection and will be analyzed upon further investigation of the data set in future research initiatives. The attitude indicator and FMA were not included in the regression and ANOVA analysis of this thesis.

Table 5. IOS Collection Data

Type	Variable
Stamp	Frame
Stamp	Time
RunInfo	Subject
RunInfo	Task
Aircraft	Lat
Aircraft	Lon
Aircraft	Alt
Aircraft	Pitch
Aircraft	Roll
Aircraft	HeadingTrue
Aircraft	TrackTrue
Aircraft	Vertical Speed
Aircraft	Ground Speed
Aircraft	V-NS
Aircraft	V-EW
Aircraft	CAS
Instruments	Rudder
Instruments	En1Throttle
Instruments	En2Throttle
Instruments	Elevator
Instruments	Aileron
Instruments	Flaps
Instruments	SBrake
Instruments	FuelFlow1
Instruments	FuelFlow2
Instruments	fuelWeight
Instruments	rad_alt
Instruments	ToeLeft
Instruments	ToeRight
Nexus	ChA
Nexus	ChB
Nexus	ChC
Nexus	ChD
Nexus	ChE
Nexus	ChF
Nexus	ChG
Nexus	ChH
ET	Head-X
ET	Head-Y
ET	Head-Z
ET	NoseV-X
ET	NoseV-Y
ET	NoseV-Z
ET	LeftEarV-X
ET	LeftEarV-Y
ET	LeftEarV-Z
ET	HeadUpV-X
ET	HeadUpV-Y
ET	HeadUpV-Z
ET	LGazeO-X
ET	LGazeO-Y
ET	LGazeO-Z
ET	LGazeV-X
ET	LGazeV-Y
ET	LGazeV-Z
ET	RGazeO-X
ET	RGazeO-Y
ET	RGazeO-Z
ET	RGazeV-X
ET	RGazeV-Y
ET	RGazeV-Z
ET	EyelidOpening
ET	WorldIntersection

Analysis of the subjective results crossed with the testing conditions indicated that the varying test conditions (Level of Automation, Land/Go Around) did yield a variance in induced workload. Workload was assessed in real time using the Bedford workload scale, and post-run using the SART situational awareness assessment and the NASA-TLX. Analysis shows that all assessments correlate together as expected and are indicative of the pilot's perceived performance and associative workload in each test run.

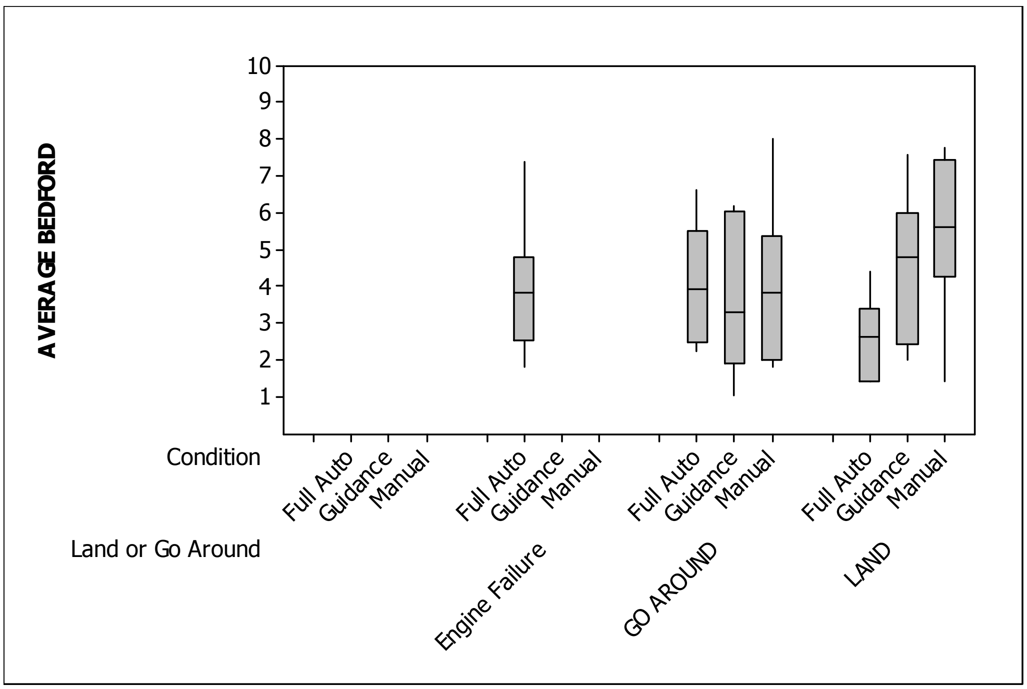


Figure 18. Boxplot of Average Bedford Score vs. Land/Go-Around, Condition

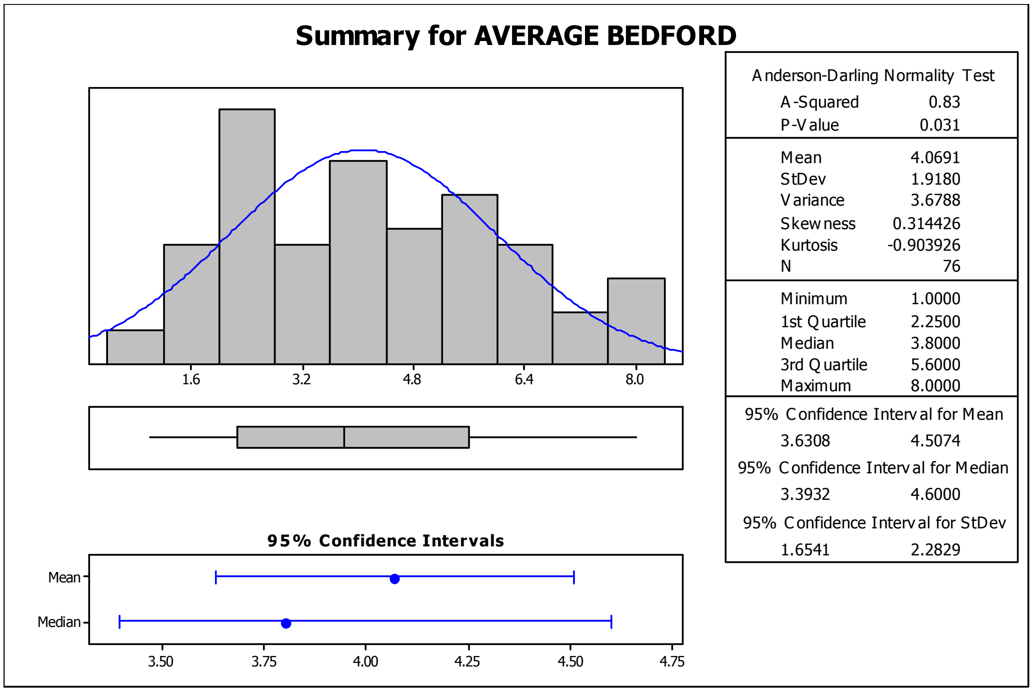


Figure 19. Average Bedford Workload Score Statistics

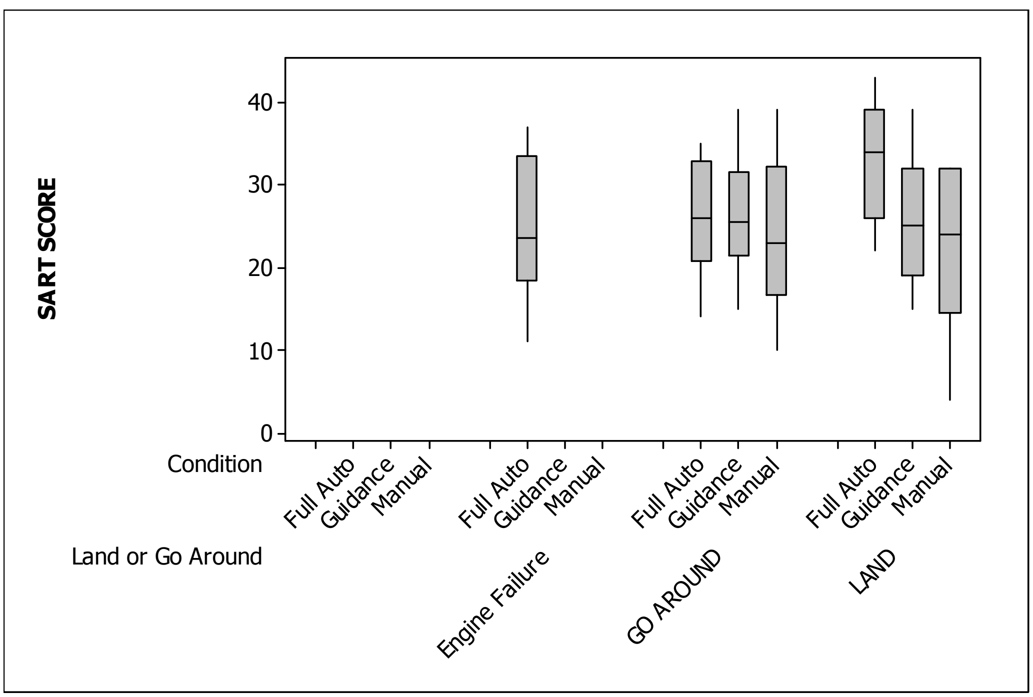


Figure 20. Boxplot of SART Score vs. Land/Go-Around, Condition

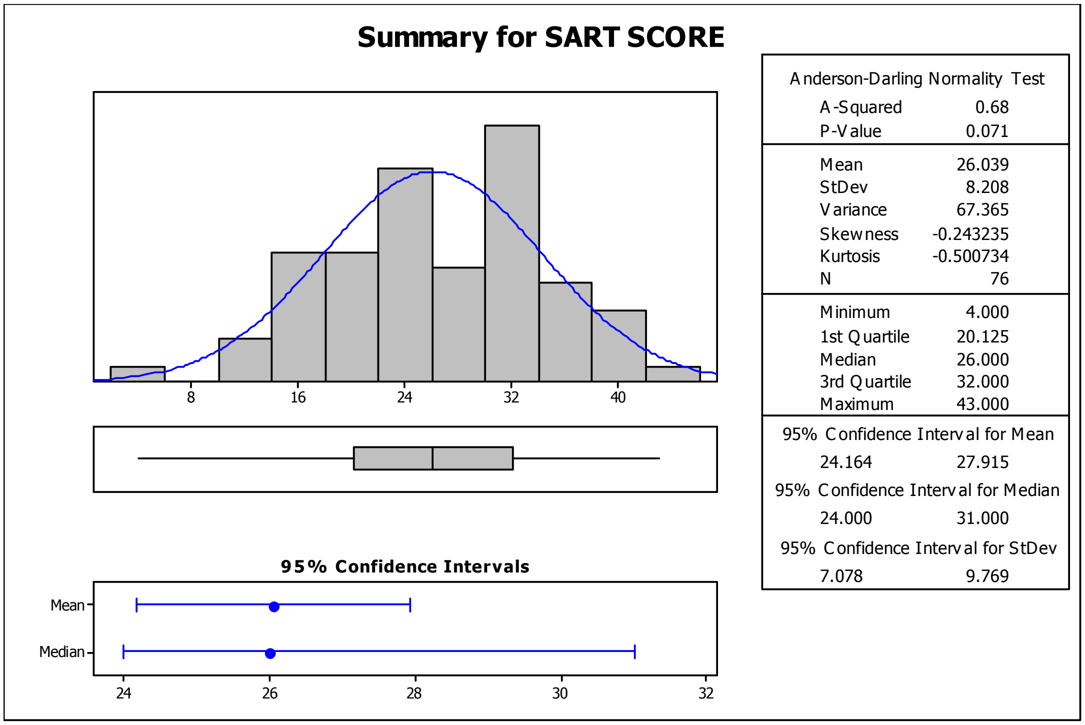


Figure 21. SART Score Statistics

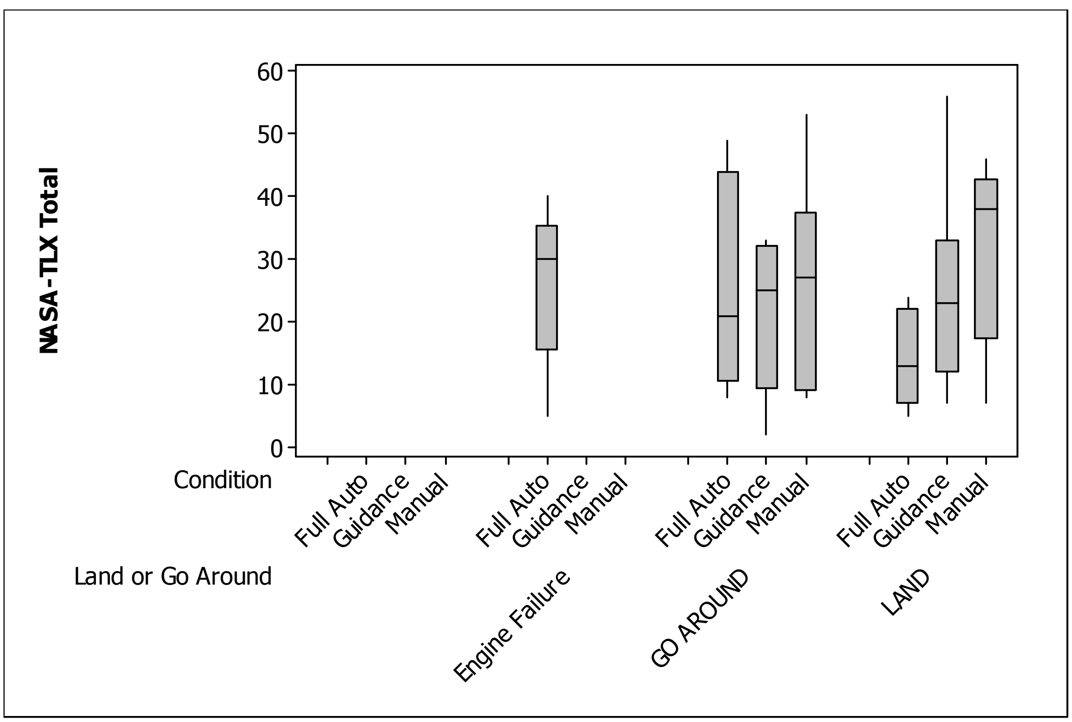


Figure 22. Boxplot of NASA-TLX Score vs. Land/Go-Around, Condition

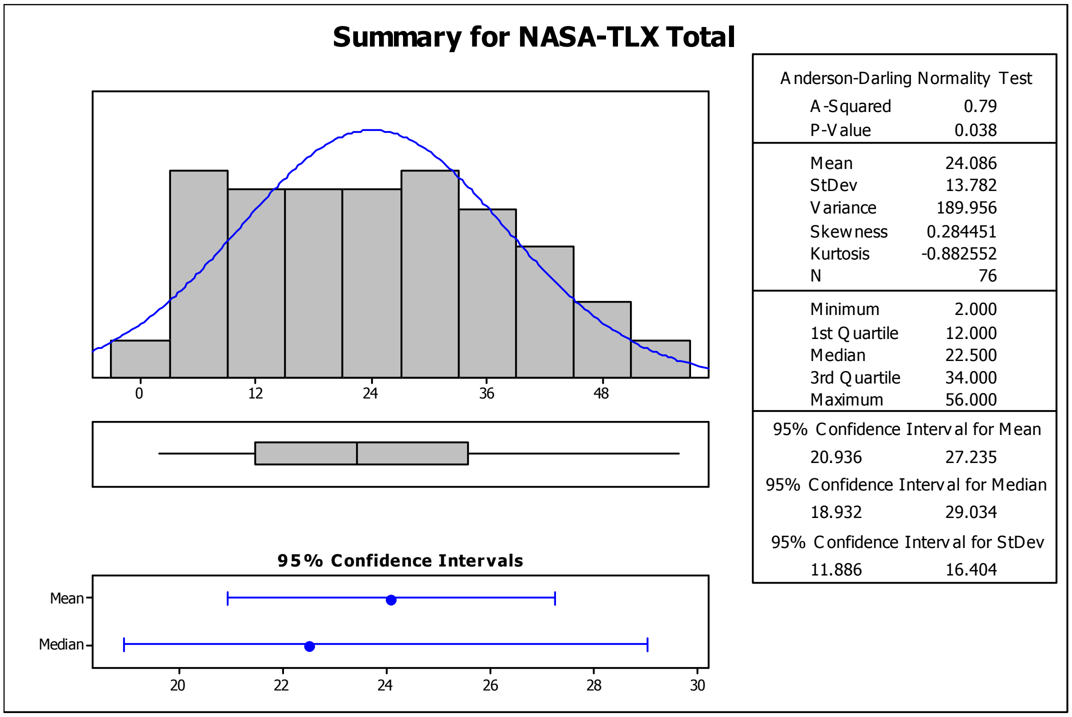


Figure 23. NASA-TLX Total Statistics

Regression of both the SART scores and NASA-TLX totals against the Average Bedford ratings indicates a statistically significant relationship of each of these subjective measures to one another. In depth analysis is done later in this chapter of several eye tracking metrics against the Bedford workload scale. Results of the regression analysis between these subjective measures is intended to provide evidence that any relationship between any eye tracking metrics analyzed applies to each subjective measure according to their respective calculated relationship.

```
The regression equation is
AVERAGE BEDFORD = 7.49 - 0.131 SART SCORE


Predictor        Coef  SE Coef      T      P
Constant       7.4856   0.6134  12.20  0.000
SART SCORE   -0.13121  0.02248  -5.84  0.000


S = 1.59785   R-Sq = 31.5%   R-Sq(adj) = 30.6%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       1   86.978  86.978  34.07  0.000
Residual Error  74  188.932   2.553
Total           75  275.910
```

Figure 24. Average Bedford vs. SART Score Regression

```
The regression equation is
AVERAGE BEDFORD = 1.28 + 0.116 NASA-TLX Total

Predictor            Coef   SE Coef      T      P
Constant           1.2817    0.2489   5.15  0.000
NASA-TLX Total   0.115729  0.008985  12.88  0.000


S = 1.07239   R-Sq = 69.2%   R-Sq(adj) = 68.7%


Analysis of Variance

Source          DF      SS      MS       F      P
Regression       1  190.81  190.81  165.92  0.000
Residual Error  74   85.10    1.15
Total           75  275.91
```

Figure 25. Average Bedford vs. NASA-TLX Total Regression

Analysis Methodology

The raw data collected by the IOS was processed using preprocessing software written to analyze the gaze vector output and to quantify it into both saccadic movements and fixations. Fixations were defined in the preprocessing software as a series of eye points falling within a 2 degree radius for greater than 300 milliseconds, with an outlier tolerance of 100 milliseconds to filter noisy data points. Filtering creates a third component, called an *Orphan*, which is a definition used to describe quick saccadic movements under 100 milliseconds that break up an individual fixation. Fixations lasting longer than 3 seconds were ignored in preprocessing calculations to filter out bad data. Saccadic movements were counted as a component linking two fixations together, broken down into distance in angular degrees.

To calculate the change in spatial spread of the fixation map/scan-path, the standard deviation of the gaze vector in X and Y components over a period of 30 seconds was determined and included as part of the output from the preprocessor. Larger standard deviations in either direction indicate a larger spread in fixation density, and therefore a higher level of entropy in the eye movement behavior of the subject, and a change in the standard eye scan pattern.

The effort to discover a correlation between eye movement behavior and pilot workload encounters two obstacles when analyzing the data set collected in this study; the frequency of pilot subjective workload responses not being identical to the frequency of collection data, creating the need for interpolation, a therefore assumed error, and portions of data that misrepresent the actual behavior of the subjects eyes. The latter can only be addressed by increasing the test population, which can be resolved by appending future data onto this data set.

The first indicated problem is approached by organizing the raw data using two methods; analysis of the 30 seconds prior to each waypoint to capture the eye movement behavior closest to the period when the pilot reported a workload, and a composite regression analysis of the average workload and averages of the eye tracking metrics across each test run. This effectively views the data from both a generic overview, indicating eye movement behavior trends across pilots, and at the highest resolution possible, by observing each pilot individually at the point of workload response.

Regression analysis is most favorable for algorithm development as it is capable of providing a direct equation to correlate the eye movement behavior. Pilots were asked to report their workload to the flight test engineers upon initial start of the simulation and upon arrival at each waypoint, totaling six data points of subjective workload for each test run (1 data point / ~2 min). The interpolation required of each regression analysis is therefore likely to ignore the individual short term experiences that pilots often encounter in standard flight.

Composite metric analysis was also performed across pilots, analyzing several eye tracking metrics for each test run as a whole. This analysis approach provides insight into the general trends in eye movement behavior based upon the composite values of the pilots' subjective workload scales, including the Bedford workload scale, the SART, and the NASA-TLX.

Metric analysis is initially reviewed by plotting each individual eye tracking metric for all pilots against Bedford workload score. This allows for visual observation of each metric and its associated trend to increasing workload as seen in Figure 26. Example Boxplot of ET Metric vs. Workload (Max HDG Fixation Duration vs. Workload). The complete set of boxplots created from the data set is available in the appendix attached at the end of this thesis.

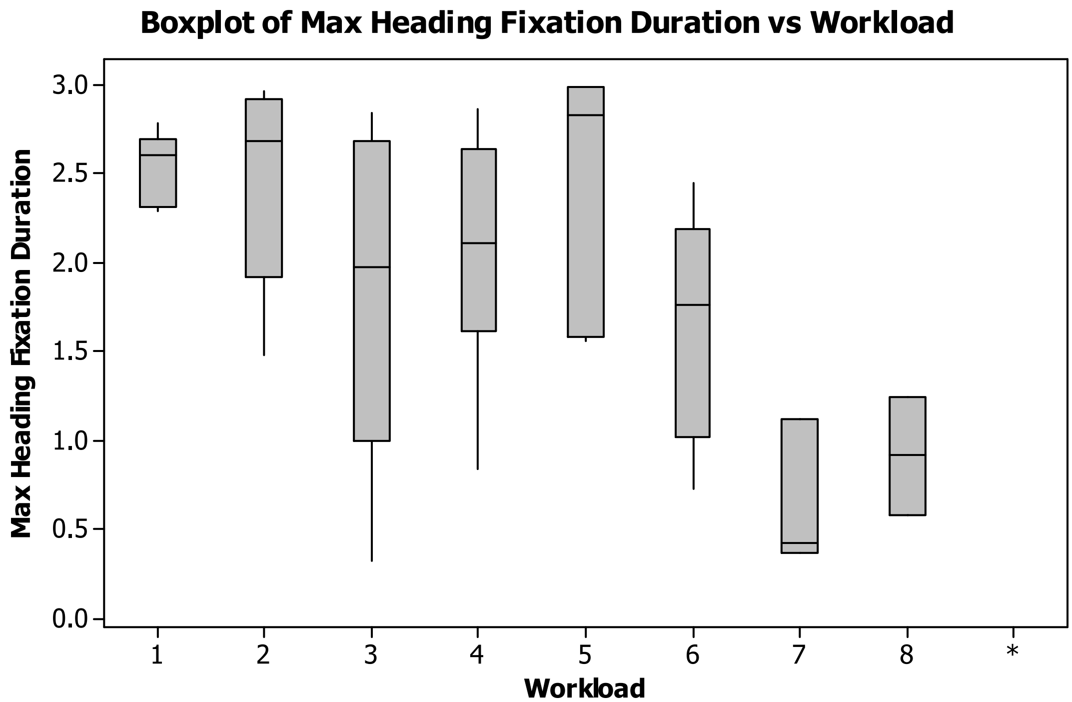


Figure 26. Example Boxplot of ET Metric vs. Workload (Max HDG Fixation Duration vs. Workload)

Metrics indicating a correlation to increasing workload were included in a repeated measures ANOVA. Bedford workload was specified as the response in a general linear model ANOVA, utilizing the eye tracking metrics as the model, and subject as the random factor. Eye tracking metrics were down-selected based upon the trends observed in initial boxplot review and consistency of the metric data in the data set. The down-selection was necessary due to include a balanced set of data to be processed, as well as the processing requirements to perform the ANOVA exceeding the limits of the computers used for analysis. Metrics included in the ANOVA are: mean fixation duration, max fixation duration, fixation frequency, mean saccade length and max saccade length.

Repeated Measures ANOVA -

General Linear Model: Workload versus Subject, Mean Fixation Du, ...

```
Factor                  Type    Levels  Values
Subject                 random      12  1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12


Analysis of Variance for Workload, using Adjusted SS for Tests

Source                          Model DF  Reduced DF    Seq SS
Subject                               11          11  196.2004
Mean Fixation Duration                76         58+  109.7476
Subject*Mean Fixation Duration       836          0+    0.0000
Max Fixation Duration                 41          0+    0.0000
Subject*Max Fixation Duration        451          0+    0.0000
Fixation Frequency                    76          0+    0.0000
Subject*Fixation Frequency           836          0+    0.0000
Mean Saccade Length                   76          0+    0.0000
Subject*Mean Saccade Length          836          0+    0.0000
Max Saccade Length                    76          0+    0.0000
Subject*Max Saccade Length           836          0+    0.0000
Error                              -4075           7   10.0000
Total                                 76          76  315.9481

+ Rank deficiency due to empty cells, unbalanced nesting, collinearity, or an
     undeclared covariate. No storage of results or further analysis will be
     done.


S = 1.19523   R-Sq = 96.83%   R-Sq(adj) = 65.64%
```

Figure 27. Eye Tracking Metric vs. Workload Repeated Measures ANOVA

Analysis of variance yielded a high R-squared value for the repeated measures model, suggesting however, did not provide further insight into the variance of the measures across subjects. This was due to unbalance in the data set values for the selected measures. Further analysis using regression models was performed to gain increased insight into the correlation and associated variance of the eye tracking measures.

Regression Analysis: Workload versus Mean Fixatio, Max Fixation, ...

```
The regression equation is
Workload = 6.23
           + 12.0 Mean Fixation Duration
           - 0.061 Max Fixation Duration
           + 0.41 Fixation Frequency
           - 0.021 Mean Saccade Length
           + 0.0210 Max Saccade Length
           - 8.33 Mean Altitude Fixation Duration
           + 0.38 Max Altitude Fixation Duration
           + 0.0953 Altitude Fixation Frequency
           - 1.81 Mean Heading Fixation Duration
           - 0.871 Max Heading Fixation Duration
           - 0.00245 Heading Fixation Frequency
           - 3.39 Mean MFD Fixation Duration
           - 2.48 Max MFD Fixation Duration
           + 8.13 MFD Fixation Frequency
           - 2.05 Mean MCP Fixation Duration
           + 1.49 Max MCP Fixation Duration
```

Predictor	Coef	SE Coef	T	P
Constant	6.233	3.623	1.72	0.109
Mean Fixation Duration	11.98	13.88	0.86	0.404
Max Fixation Duration	-0.0608	0.6174	-0.10	0.923
Fixation Frequency	0.411	1.423	0.29	0.777
Mean Saccade Length	-0.0209	0.1130	-0.18	0.856
Max Saccade Length	0.02097	0.01934	1.08	0.298
Mean Altitude Fixation Duration	-8.326	7.021	-1.19	0.257
Max Altitude Fixation Duration	0.375	1.024	0.37	0.720
Altitude Fixation Frequency	0.09534	0.06589	1.45	0.172
Mean Heading Fixation Duration	-1.805	4.336	-0.42	0.684
Max Heading Fixation Duration	-0.8708	0.7037	-1.24	0.238
Heading Fixation Frequency	-0.002448	0.007714	-0.32	0.756
Mean MFD Fixation Duration	-3.389	5.538	-0.61	0.551
Max MFD Fixation Duration	-2.4792	0.8313	-2.98	0.011
MFD Fixation Frequency	8.135	3.847	2.11	0.054
Mean MCP Fixation Duration	-2.049	3.492	-0.59	0.567
Max MCP Fixation Duration	1.4854	0.7349	2.02	0.064

S = 1.11789   R-Sq = 73.7%   R-Sq(adj) = 41.4%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	16	45.621	2.851	2.28	0.070
Residual Error	13	16.246	1.250		
Total	29	61.867			

Figure 28. Eye Tracking Metrics vs. Workload Regression Model

Regression analysis yields a model with moderately high correlation to workload with nearly statistically significant output (R-sq = 73.7%, P = 0.07). This is suggests that certain metrics utilized in the regression model are capable of correlating to workload.

Some components were more statistically significant than others, particularly metrics specific to regions of interest, such as the MFD fixation frequency (P=0.054) and Max MCP fixation duration (P = 0.064). These metrics and metrics specific to a given region of interest indicate a significantly higher level of significance to the overall regression model. This provides insight suggesting that the workload on the pilot changes the pilots eye movement behavior specific to a given instrument, likely dependent on the situation inducing the workload, such as a specific task.

To determine the effect of task on workload, a repeated measures ANOVA was performed to identify the variance of the task across pilots against workload. This was performed in an effort to understand the connection to flight task and a given workload. The flight tasks were defined previously as the independent variables *condition* and *land or go around*. The condition was broken down into two binary sub categories; F/D on or off and Autopilot on or off. This was done to more clearly specify what flight mode state the aircraft was in for the specified test run.

Repeated Measures ANOVA – Task against Workload

General Linear Model: Workload versus Subject, F/D, ...

Factor	Type	Levels	Values
Subject	random	12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
F/D	fixed	2	OFF, ON
Autopilot	fixed	2	OFF, ON
Land or Go Around	fixed	3	Engine Failure, GO AROUND, LAND

Analysis of Variance for Workload, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P	
Subject	11	217.274	129.694	11.790	282.97	0.989	x
F/D	1	19.201	4.083	4.083	3.77	0.078	
Subject*F/D	11	13.385	11.917	1.083	0.53	0.863	
Autopilot	1	9.025	12.000	12.000	5.87	0.034	
Subject*Autopilot	11	24.008	22.500	2.045	1.00	0.473	
Land or Go Around	2	3.250	3.250	1.625	3.43	0.050	
Subject*Land or Go Around	22	10.417	10.417	0.473	0.23	0.999	
Error	24	49.000	49.000	2.042			
Total	83	345.560					

x Not an exact F-test.

S = 1.42887 R-Sq = 85.82% R-Sq(adj) = 50.96%

Figure 29. Task vs. Workload Repeated Measures ANOVA

Repeated measures ANOVA results of task versus workload indicate that Autopilot (R-sq = 85.82%, P=0.034) is a statistically significant factor correlating to workload. F/D is also a factor, however, not to the same degree as the autopilot condition. The Land or Go Around decision also provided significant effect on workload (P = 0.05). Overall results of the ANOVA indicate an R-sq value of 85.82%, indicating a relatively strong correlation to workload. This indicates that aircraft mode state (pilot task) plays a significant role in determining a pilot's workload. Including the aircraft mode state in the model to classify workload through eye movement behavior could potentially aid in improving the quality of the overall classification model developed.

A repeated measures ANOVA combining both aircraft mode state and the eye tracking measures was performed to determine if there was an improvement to the regression model by including aircraft state information to the eye tracking model.

General Linear Model: Workload versus Subject, Mean Fixation Du, ...

Factor	Type	Levels	Values
Subject	random	12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
F/D Bi	fixed	2	0, 1
Autopilot Bi	fixed	2	0, 1

Analysis of Variance for Workload, using Adjusted SS for Tests

Source	Model DF	Reduced DF	Seq SS
Subject	11	11	196.2004
Mean Fixation Duration	76	58+	109.7476
Subject*Mean Fixation Duration	836	0+	0.0000
Max Fixation Duration	41	0+	0.0000
Subject*Max Fixation Duration	451	0+	0.0000
Fixation Frequency	76	0+	0.0000
Subject*Fixation Frequency	836	0+	0.0000
Mean Saccade Length	76	0+	0.0000
Subject*Mean Saccade Length	836	0+	0.0000
Max Saccade Length	76	0+	0.0000
Subject*Max Saccade Length	836	0+	0.0000
F/D Bi	1	1	0.7000
Subject*F/D Bi	11	0+	0.0000
Autopilot Bi	1	1	4.8000
Subject*Autopilot Bi	11	0+	0.0000
Error	-4099	5	4.5000
Total	76	76	315.9481

\+ Rank deficiency due to empty cells, unbalanced nesting, collinearity, or an undeclared covariate. No storage of results or further analysis will be done.

S = 0.948683   R-Sq = 98.58%   R-Sq(adj) = 78.35%

Figure 30. Task + ET Metrics vs. Workload Repeated Measures ANOVA

Results contrasted to the ANOVA R-sq values of the eye tracking metrics themselves indicate an improvement in both the R-squared value as well as the R-squared adjusted value. This suggests that the general linear model is improved by including the aircraft mode state. However, due to unbalance in the data set values for each metric included in the ANOVA, further variance analysis and statistical significance was not established. Regression analysis on the eye tracking metrics used in the regression model earlier (Figure 28. Eye Tracking Metrics vs. Workload Regression Model) was performed again with the inclusion of the aircraft mode state.

Regression Analysis: Workload versus Mean Fixatio, Max Fixation, ...

```
The regression equation is
Workload = 7.69 + 11.9 Mean Fixation Duration - 0.134 Max Fixation Duration
           - 0.54 Fixation Frequency - 0.050 Mean Saccade Length
           + 0.0211 Max Saccade Length - 7.49 Mean Altitude Fixation Duration
           + 0.075 Max Altitude Fixation Duration
           + 0.0962 Altitude Fixation Frequency
           - 2.71 Mean Heading Fixation Duration
           - 0.509 Max Heading Fixation Duration
           - 3.38 Mean MFD Fixation Duration - 2.09 Max MFD Fixation Duration
           + 6.63 MFD Fixation Frequency - 1.89 Mean MCP Fixation Duration
           + 1.31 Max MCP Fixation Duration - 0.681 F/D Bi - 0.133 Autopilot Bi


30 cases used, 54 cases contain missing values
```

Predictor	Coef	SE Coef	T	P
Constant	7.688	3.393	2.27	0.043
Mean Fixation Duration	11.88	12.72	0.93	0.369
Max Fixation Duration	-0.1342	0.6100	-0.22	0.830
Fixation Frequency	-0.541	1.672	-0.32	0.752
Mean Saccade Length	-0.0500	0.1180	-0.42	0.679
Max Saccade Length	0.02111	0.01878	1.12	0.283
Mean Altitude Fixation Duration	-7.488	7.171	-1.04	0.317
Max Altitude Fixation Duration	0.0753	0.7384	0.10	0.921
Altitude Fixation Frequency	0.09616	0.05858	1.64	0.127
Mean Heading Fixation Duration	-2.714	2.002	-1.36	0.200
Max Heading Fixation Duration	-0.5086	0.8306	-0.61	0.552
Mean MFD Fixation Duration	-3.385	5.682	-0.60	0.562
Max MFD Fixation Duration	-2.0925	0.9587	-2.18	0.050
MFD Fixation Frequency	6.629	4.236	1.57	0.144
Mean MCP Fixation Duration	-1.889	3.397	-0.56	0.588
Max MCP Fixation Duration	1.3123	0.7234	1.81	0.095
F/D Bi	-0.6811	0.9011	-0.76	0.464
Autopilot Bi	-0.1328	0.6815	-0.19	0.849

S = 1.12717   R-Sq = 75.4%   R-Sq(adj) = 40.4%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	17	46.620	2.742	2.16	0.090
Residual Error	12	15.246	1.271		
Total	29	61.867			

Figure 31. Task + ET Metrics vs. Workload Regression

Results of the combined regression analysis indicate an overall decrease in statistical significance for the regression model. The overall R-squared value increases, however, the R-squared adjusted value decreases as would be expected when adding more variables to the model. Without an increase in the adjusted R-squared value, the significance to adding the aircraft mode state is minimal to the model generated. F/D and Autopilot state modes both indicate a P value greater than 0.46 providing no statistical significance when combined with the metrics presently included in the model.

Results Conclusion

Development of a workload algorithm driven by eye tracking metrics is the ultimate goal in aiding the initiative to classify operator state in real time flight deck operations. Based upon this data set of pilot eye movements there is a wealth of information that can continue to be mined for further insights into such eye movement behaviors. Information taken from this analysis of the eye movement behavior trends provides a significant starting point to develop a fully functional workload algorithm based upon eye tracking metrics. Analysis of task and eye movement behaviors individually indicate that each are associated to workload in some capacity, as is shown in the repeated measures and regression analysis (Figure 27. Eye Tracking Metric vs. Workload Repeated Measures ANOVA; Figure 29. Task vs. Workload Repeated Measures ANOVA). Whether the two information sources can be combined to create an increasingly effective model to classify workload is still uncertain. Several eye tracking metrics indicated statistical significance or near statistical significance to the regression model, all of which were eye movement behaviors specific to a given area of interest, such as *Max MFD Fixation Frequency* (see Figure 28. Eye Tracking Metrics vs. Workload Regression Model). To this extent, further research initiatives must be taken to determine which combination of areas of interest metrics are the most useful in classifying pilot workload.

CHAPTER 5.
CATS INTEGRATION

Cognitive Avionics Tool-Set (CATS)

The Cognitive Avionics Tool-Set (CATS) is a software application that provides a graphical user interface to organizing sets of physiological data. Developed by Blaze Keller of the Operator Performance Laboratory, it has been used in a beta version format for several studies. The ultimate goal of CATS is to be able to compile several sources of physiological data and generate analysis outputs of that data in a usable and presentable form. Beyond this goal, taking all of the same physiological inputs (EEG, ECG, respiration rate, body temp, eye tracking, etc.) real-time analysis will provide instant feedback of pilot workload (Schnell, Keller, & Macuda, Application of the Cognitive Avionics Tool Set (CATS) in Airborne Operator State Classification, 2007). CATS has been utilized in a study done by the Operator Performance Laboratory in collaboration with the National Research Council (NRC) of Canada. Initial intention of CATS is to be used on avionics platforms as was done in a rotorcraft study in Ottawa, Ontario were physiological measurements were fed into CATS and organized for data analysis (Schnell, Keller, & Macuda, 2007). Other applications can utilize CATS as well due to the underlying premise of CATS utility is to classify workload based upon physiological measurement, such as pilot training effectiveness (Schnell, Keller, & Poolman, Quality of training effectiveness assessment (QTEA); a Neurophsiologically based method to enhance flight training, 2008). The underlying research which drives the classification model however, is specific to flight deck operations.

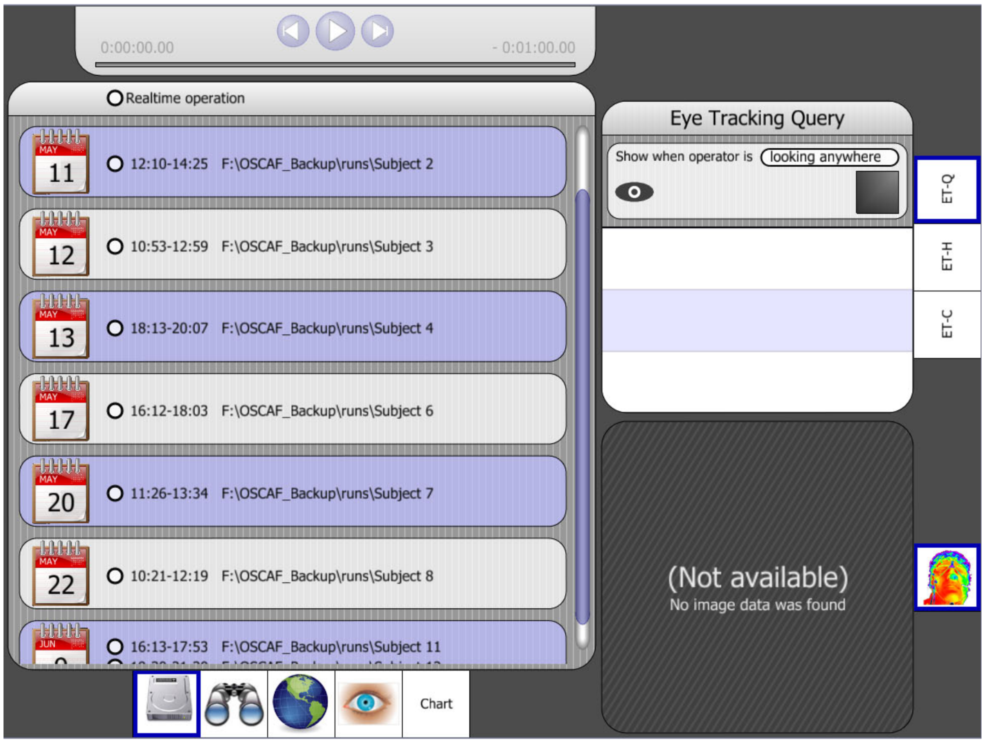


Figure 32. CATS File Selection Window

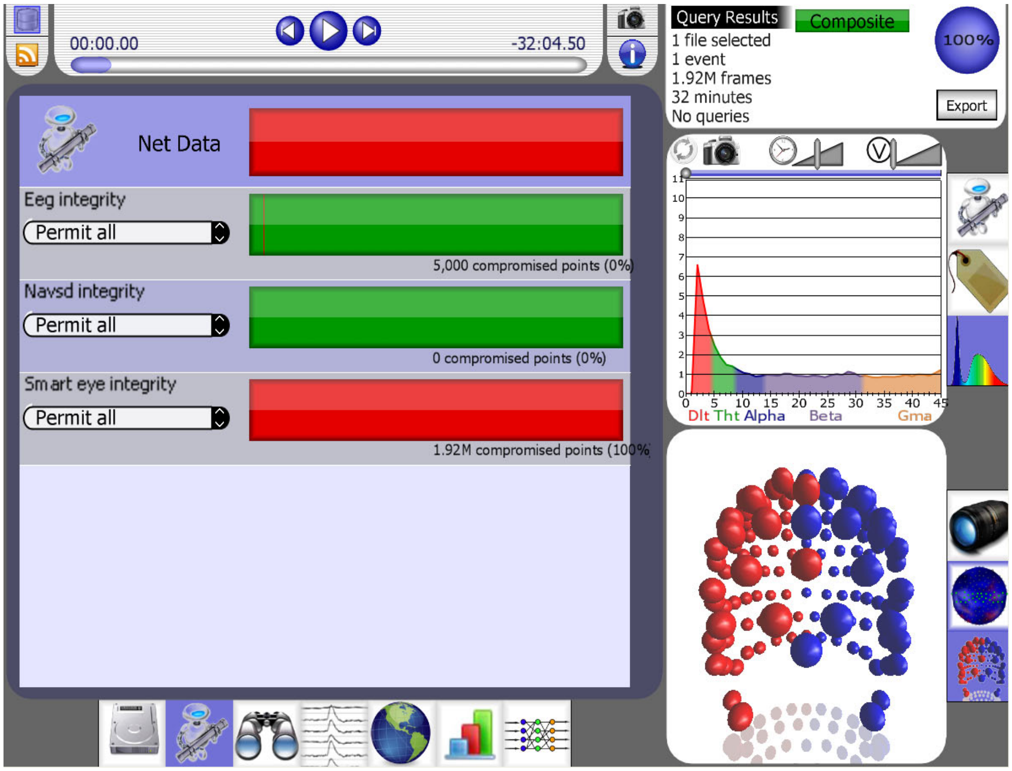


Figure 33. CATS Data Integrity Window

Data integrity is monitored by CATS by assessing the IOS recorded files and checking for gaps in the data. Data is then permitted or denied into the CATS analysis depending on user definition within the interface. Compromised data points can either be permitted to exist as gaps in the data set analysis or ignored altogether.

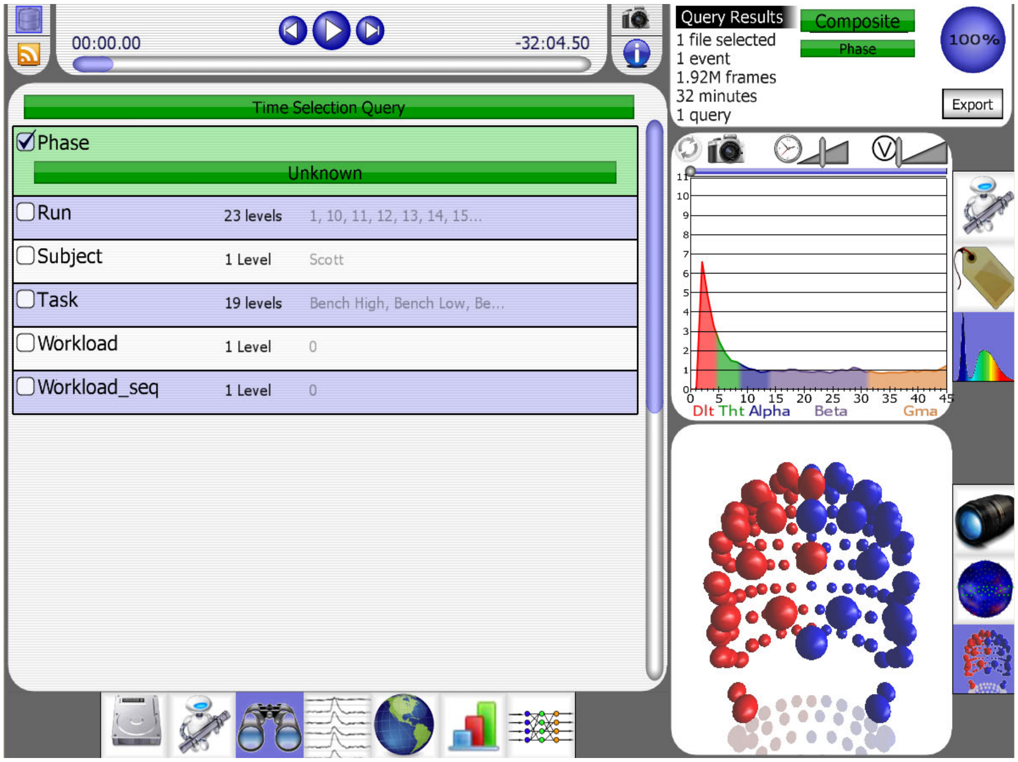


Figure 34. CATS Data Query Window

Data sets within CATS can be further broken down by querying the data in several ways. Depending on the tags associated with the data set, CATS can be programmed to split the data depending on these tags and perform analysis strictly on that particular section of data as specified by the user. This is very beneficial in eye tracking analysis that discriminates between phases of flight and task specific operations and their associated workloads.

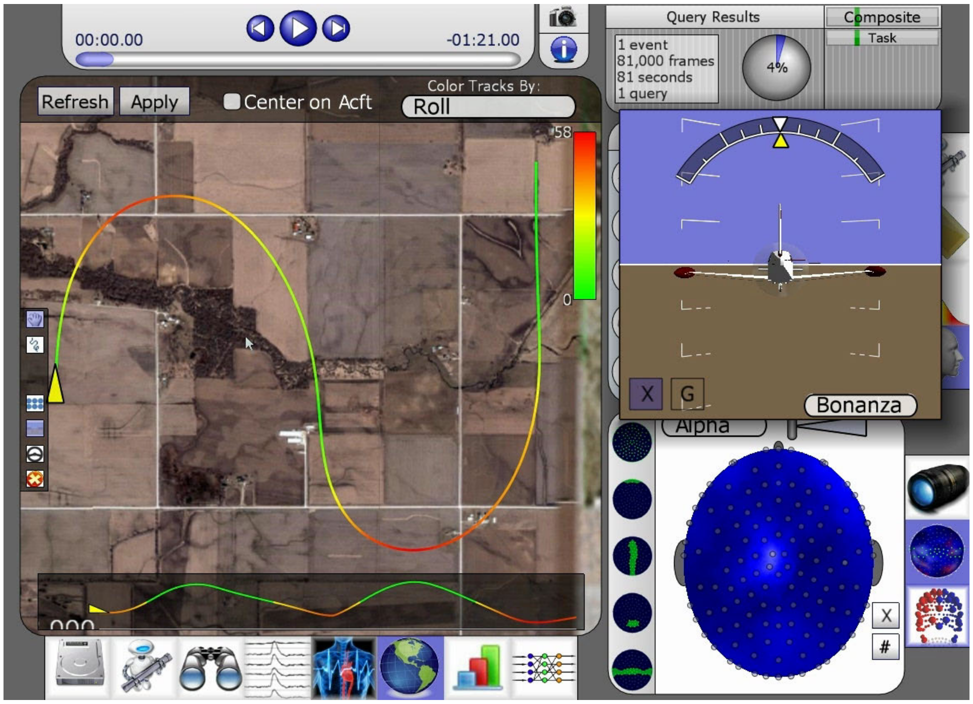


Figure 35. CATS World Viewer Window

CATS incorporates a world viewer that is created using aircraft state information embedded in the IOS output files. This is particularly useful when selecting particular sections of flight and performing analysis strictly on the data points associated with the region selected. Aircraft state is further visible by tracking the flight path and color designating particular aspects of flight, such as roll (shown in Figure 35. CATS World Viewer Window), altitude, speed, reported workload, or any of the user specified query-able tasks specified in the data set.

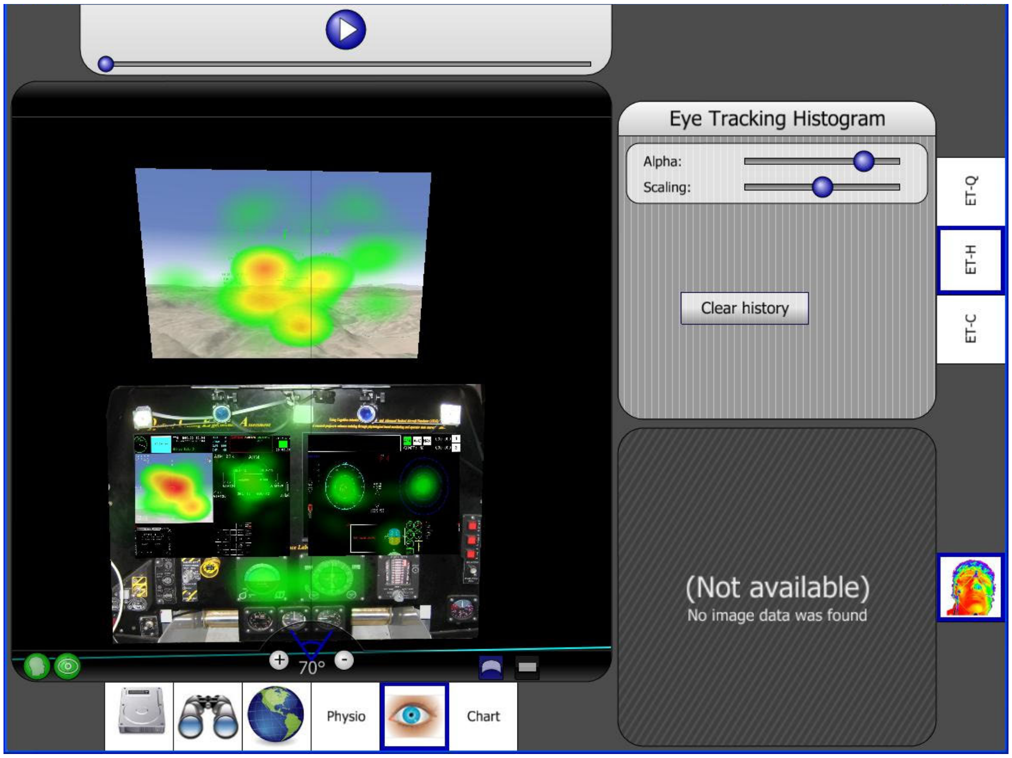


Figure 36. CATS Eye Tracking Histogram Window

Specific to eye tracking, heat mapping of fixation maps is also performed within CATS to aid in identifying scan patterns and particular areas of interest over a scaled amount of time specified in CATS user interface. With implementation of empirical data analysis specific to eye gaze fixations and scan pattern, quantitative analysis will be an available output from the CATS software.

Algorithm Implementation

To fuel CATS' ability to perform analysis on each of its physiological inputs, groundwork must be completed to determine what forms of analysis should be made and what metrics are usable for meaningful analysis. This thesis provides CATS with useful information pertaining to the eye tracking facet of CATS' physiological analysis suite. Acquisition and analysis of empirical data creates algorithms for each metric, and ultimately one metric to assess workload based upon the pertinent eye tracking metrics.

Real-Time Workload Estimation

CATS currently utilizes neural analysis, eye tracking, heart rate (ECG), and flight performance as general metrics that feed an overall workload estimation of the subject being analyzed. Development of regression models in eye tracking is utilized in CATS from this research, derived from empirical data collected in this study. For real time assessment of the pilots' fixation behavior, the average duration of fixations can be calculated for a window of 15 seconds, which typically includes a series of 10 to 20 fixations sufficient enough to provide a statistically significant average. The real time fixation behavior variables are then assessed based upon empirical analysis following the results of this research initiative with coefficients dependent on relativity to the normalization of these behaviors.

Utility of Algorithm for Real-Time Classification

The regression models developed based upon the composite results of this study is statistically significant and can be utilized as a classifier algorithm to be validated in real-time assessment tests in future studies. See **Error! Reference source not found.**Figure 26. Subject 2 Waypoint Regression Analysis, **Error! Reference source not found.**Figure 27. Subject 7 Waypoint Regression Analysis and **Error! Reference source not found.**Figure 31. Fixation Frequency Composite Regression. The coefficients relating each metric analyzed are the important components to generating a general real-time classification algorithm.

For analysis of real-time classification, it is recommended to use a window of time to perform general statistics of the various metrics that make sense. Average fixation duration was calculated over a moving time frame of 15 seconds to be able to capture enough fixations to produce a significant average of the metric. Entropy was calculated with a moving time frame of 30 seconds, since it is a metric assessing the variability that exists in a scan pattern or the spread of fixations. Shorter time frames for this metric will not provide enough time for a pattern to be recognizable, yielding no significance to the standard deviation values, but too long of a time frame will not be capable of observing the short term changes in fixations that occur in flight deck operations.

Industry Utilization of Operator State Classification Information

There are several applications that are capable of utilizing real-time operator state classification. Training of pilots can be enhanced by importing knowledge of the student's workload, allowing the instructor to increase or decrease the pace of the training to maximize the efficiency of the training for the student based upon their cognitive capacity. Allowing the avionics of flight decks to be aware of the pilot's cognitive state provides an entirely new avenue for avionics to follow; adaptive automation systems, enhanced visual ergonomics that adapt to rare situations such as unusual attitude, pilot attention retention systems, sleep mitigation systems, etc.

CHAPTER 6.
FUTURE RESEARCH

Further Initiatives to Be Pursued

Analysis of potentially useful metrics, such as eye blinks should be pursued. Eye blinks were not analyzed due to eye tracker outputs not transmitting the correct data to be recorded in the data set. Unfortunately this was unrecoverable for any of the subjects in this study, and it still holds strict interest due to eye blink as a metric being a very rich source of operator state information in previous studies.

Continued research of the present data set could be pursued to further the interaction effects of the various areas of interest. Further preprocessing of the data must be completed to fully fill the data set so balanced ANOVAs can be performed to gain full insight of variance across subjects for all eye tracking metrics. A stepwise regression would also be beneficial in determining which metrics yield the greatest impact on the regression model against workload. Validation of the data set regression models should also be completed to determine the overall effectiveness of a developed model based upon this data set.

A similar study could be performed with a new method to induce workload and collect the subjective baseline results at a higher resolution than was done with the Bedford workload ratings collected in this study (1 data point / 2 min). A possible approach would include shorter test runs with a precisely induced workload enforced upon the pilot. A post run subjective response would be sufficient to produce a subjective baseline to regress against. This is necessary to attain increasingly accurate real-time analysis algorithms for any physiological response system such as an eye tracker. A bottom up approach study could be done that induces workload in a situation by situation manner that requires pilots to react and that reaction could tag a set of data and their associative metrics. Bottom line requires a closing of the gap between data collection rates and subjective workload response rates to limit the error brought about by regression interpolation of real-time metrics.

This study provides a simple insight into the trends of eye movement metrics as they respond to induced workload in a cockpit performing an approach task. Further studies to determine which metrics are useful in classifying workload during specific tasks and which metrics classify workload generically can still be completed. Further research initiatives can also be done to assess the connection between standard eye movement behaviors in a flight deck as they pertain to individual tasks versus workload. It is believed that certain tasks performed on the flight deck induce specific eye movement behaviors. If this is the case, it is theoretically possible to assume that changes in expected eye tracking behavior may occur depending on the flight task, such as cruising and performing an approach.

APPENDIX

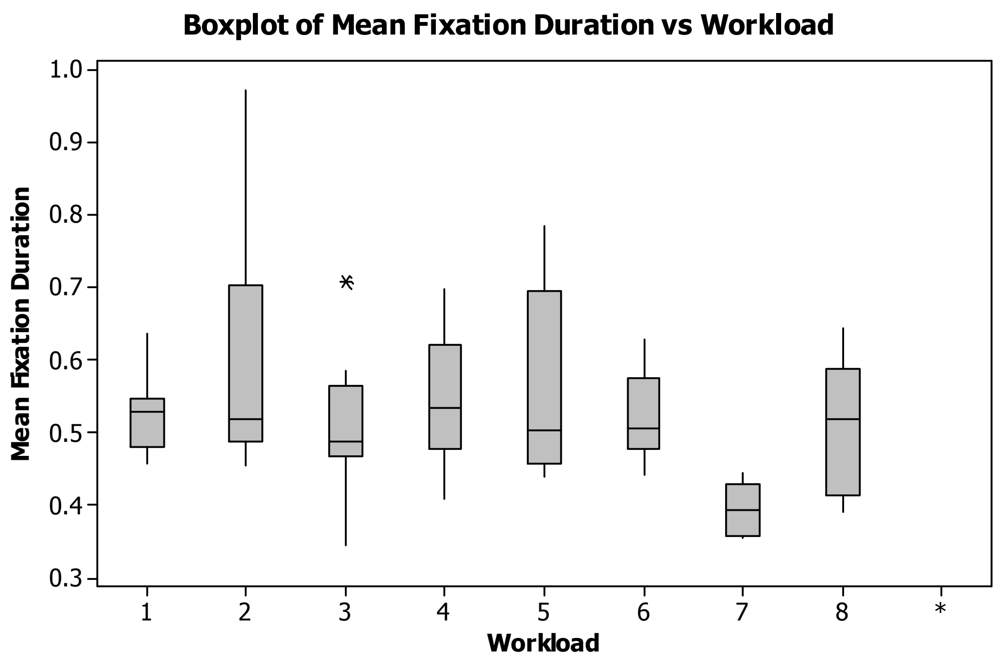


Figure A1. Mean Fixation Duration vs. Workload Boxplot

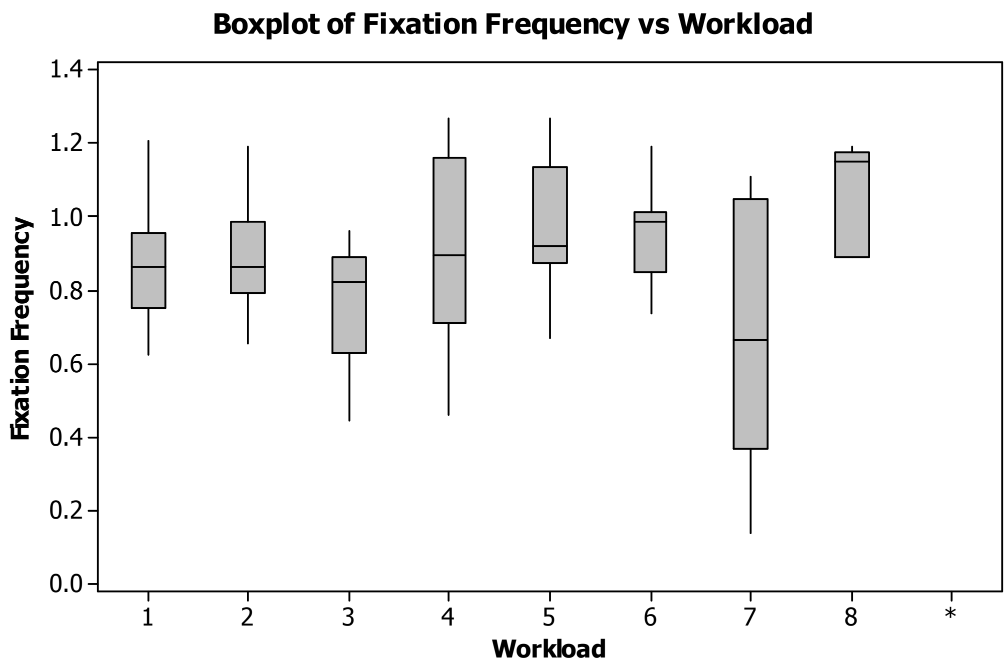


Figure A2. Global Fixation Frequency vs. Workload Boxplot

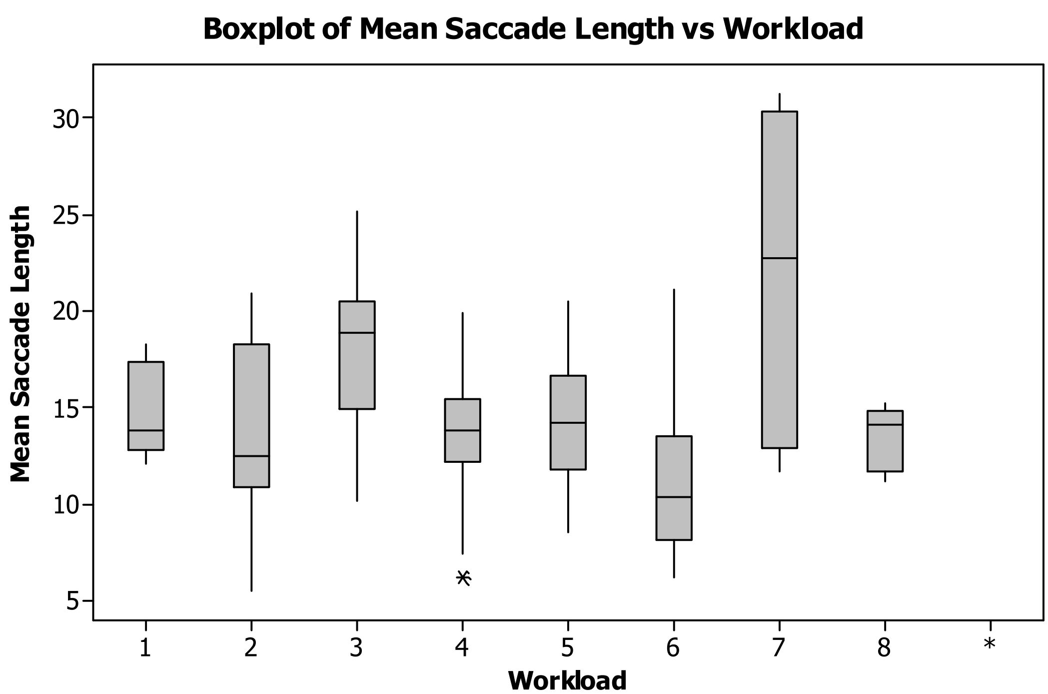


Figure A3. Mean Saccade Length vs. Workload Boxplot

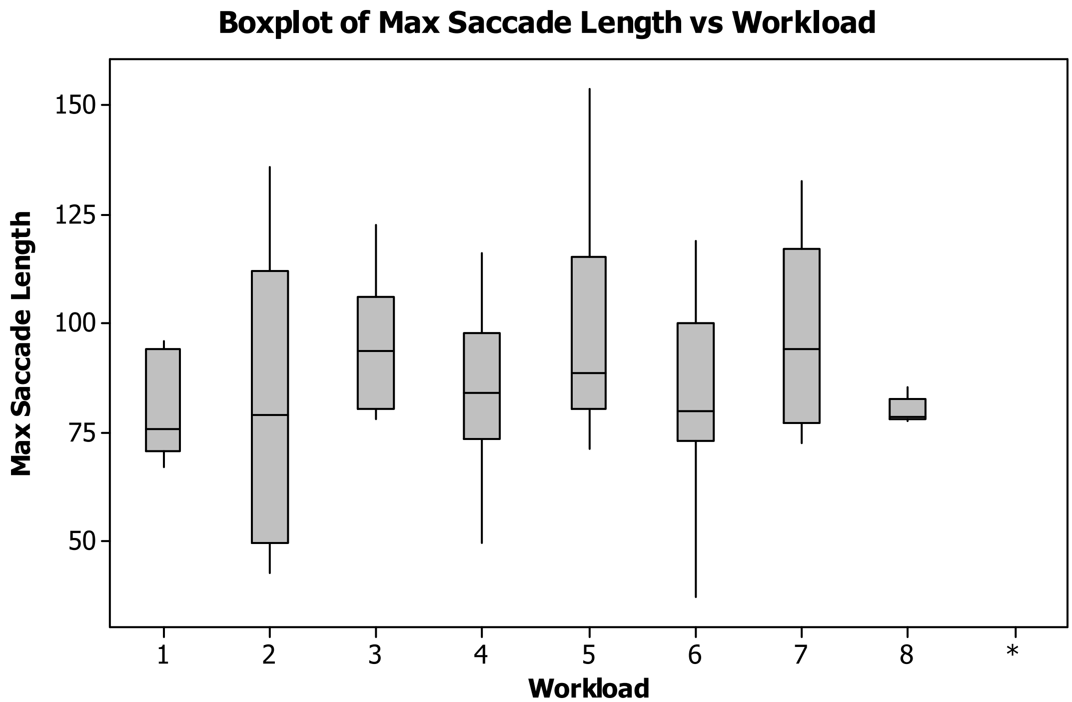


Figure A4. Max Saccade Length vs. Workload Boxplot

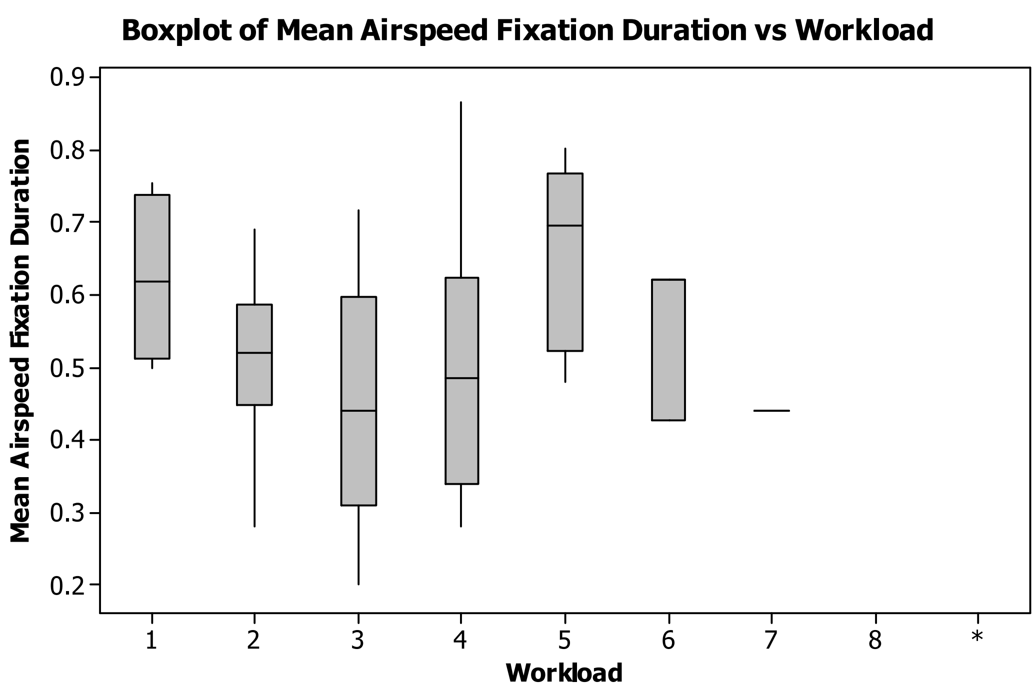


Figure A5. Mean Airspeed Fixation Duration vs. Workload Boxplot

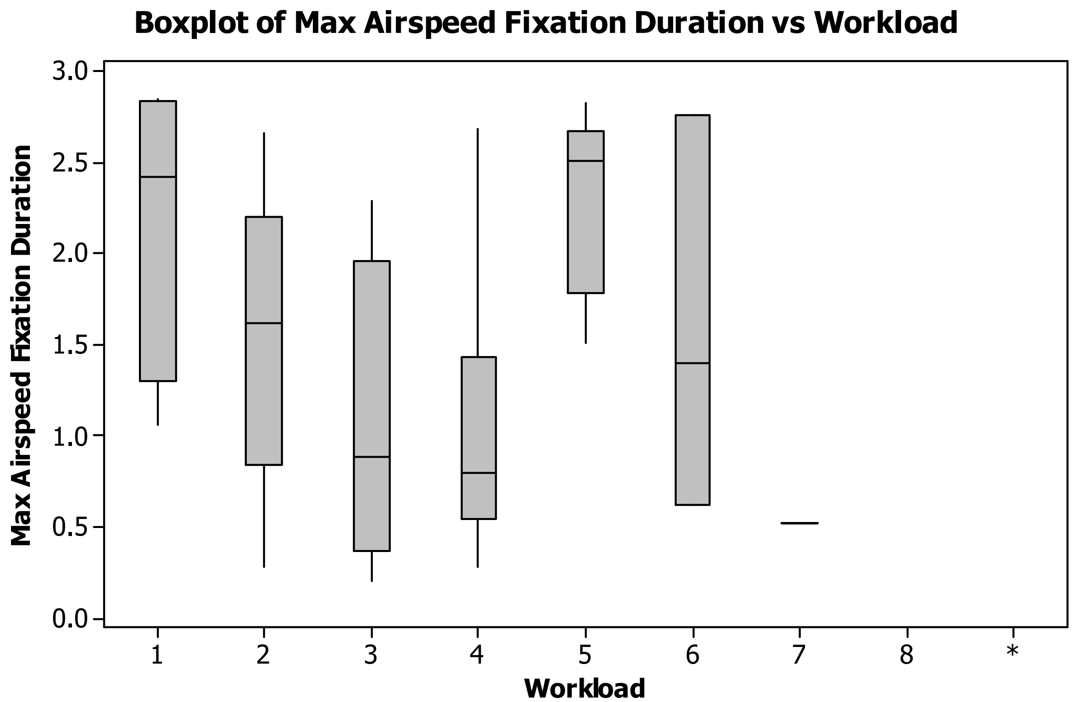


Figure A6. Max Airspeed Fixation Duration vs. Worklaod Boxplot

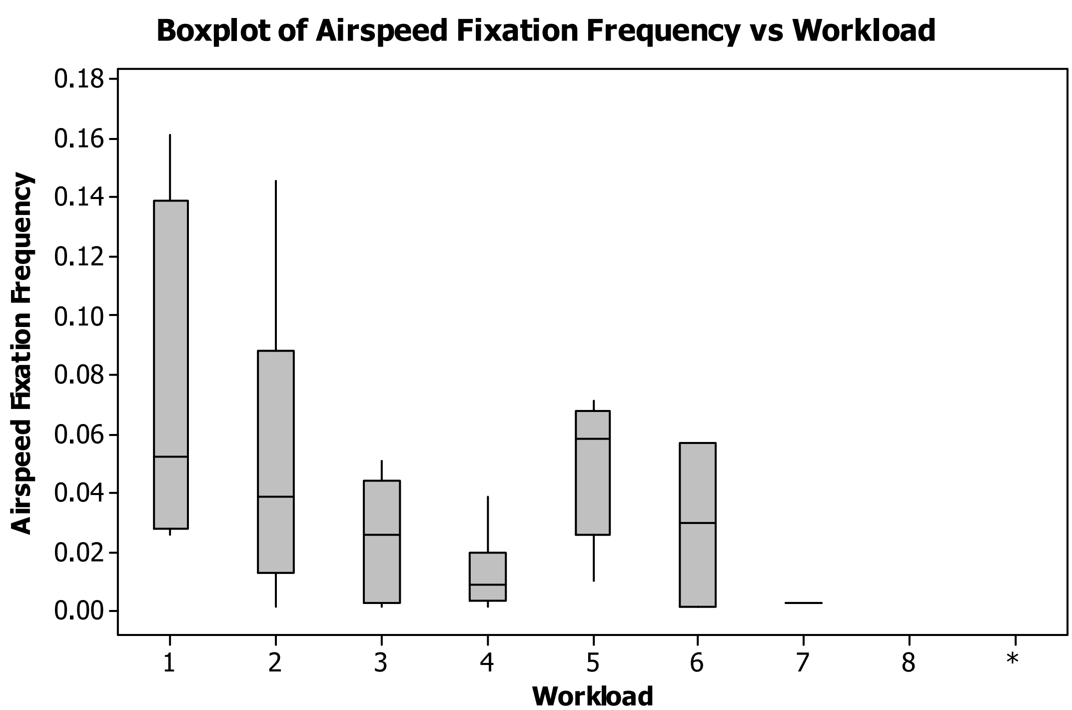


Figure A7. Airspeed Fixation Frequency vs. Workload Boxplot

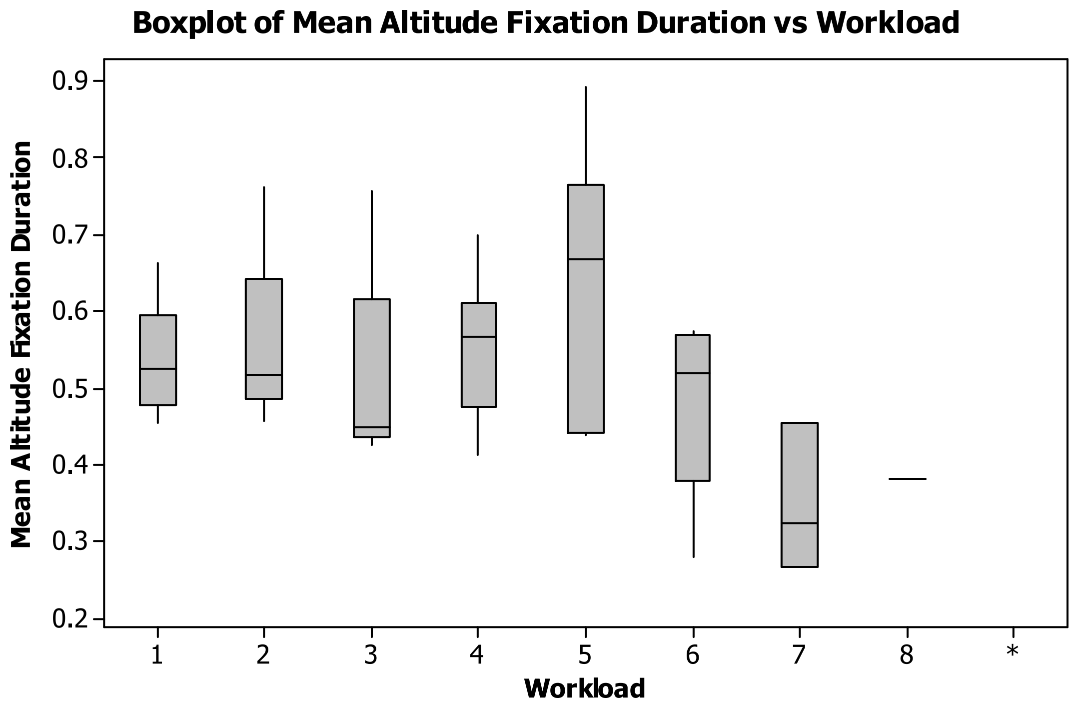


Figure A8. Mean Altitude Fixation Duration vs. Workload Boxplot

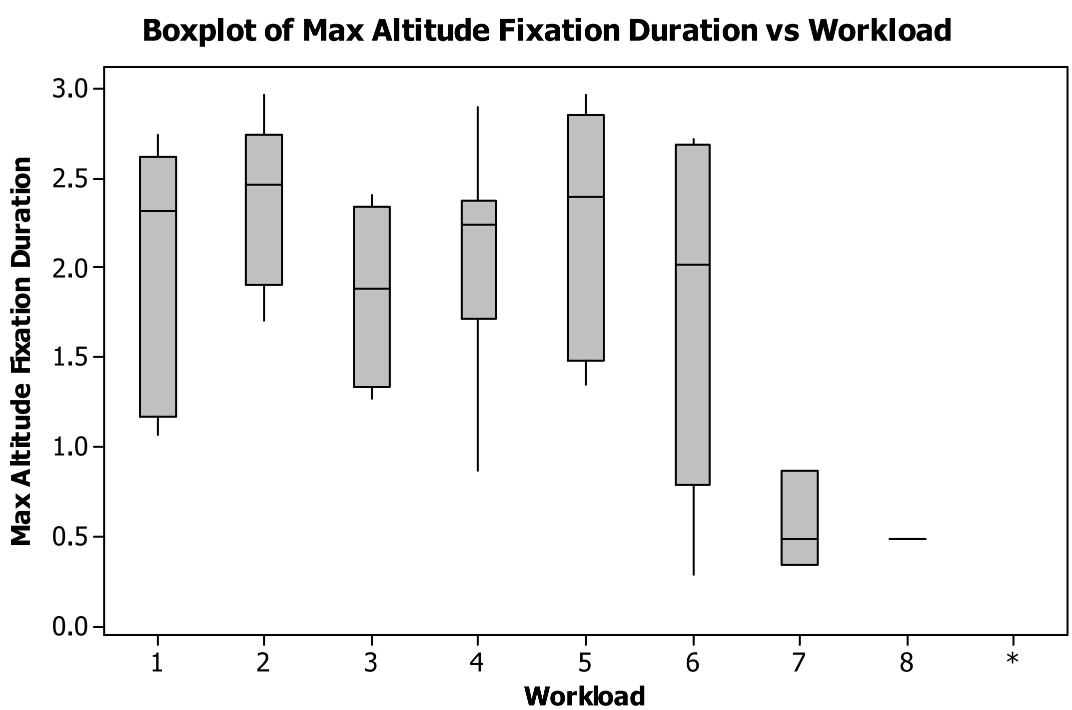


Figure A9. Max Altitude Fixation Duration vs. Workload Boxplot

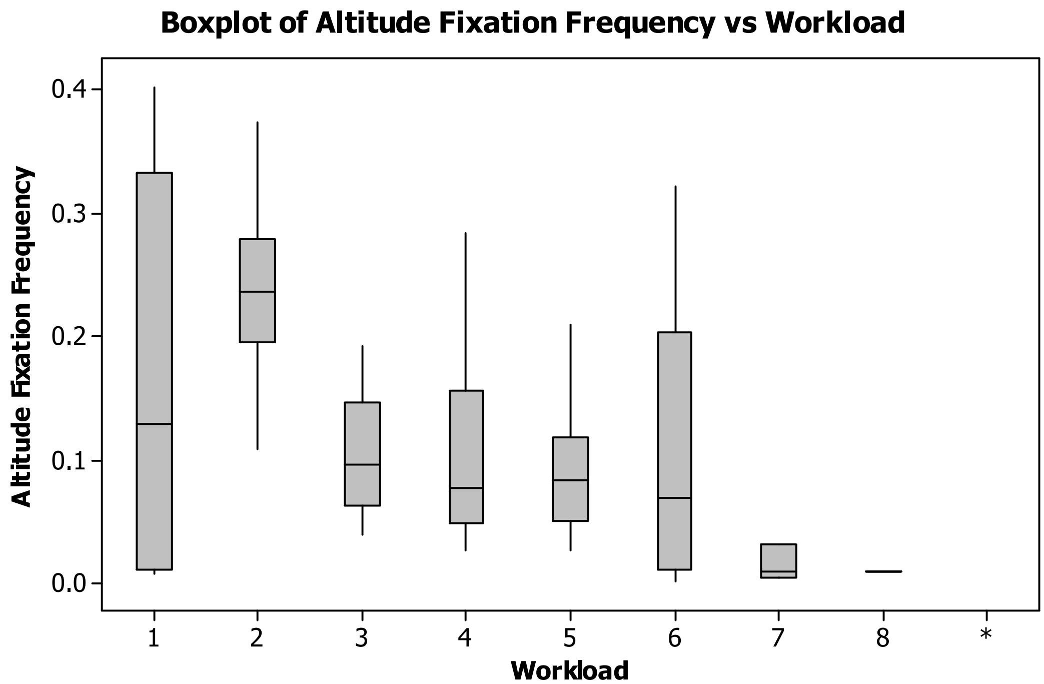


Figure A10. Altitude Fixation Frequency vs. Workload Boxplot

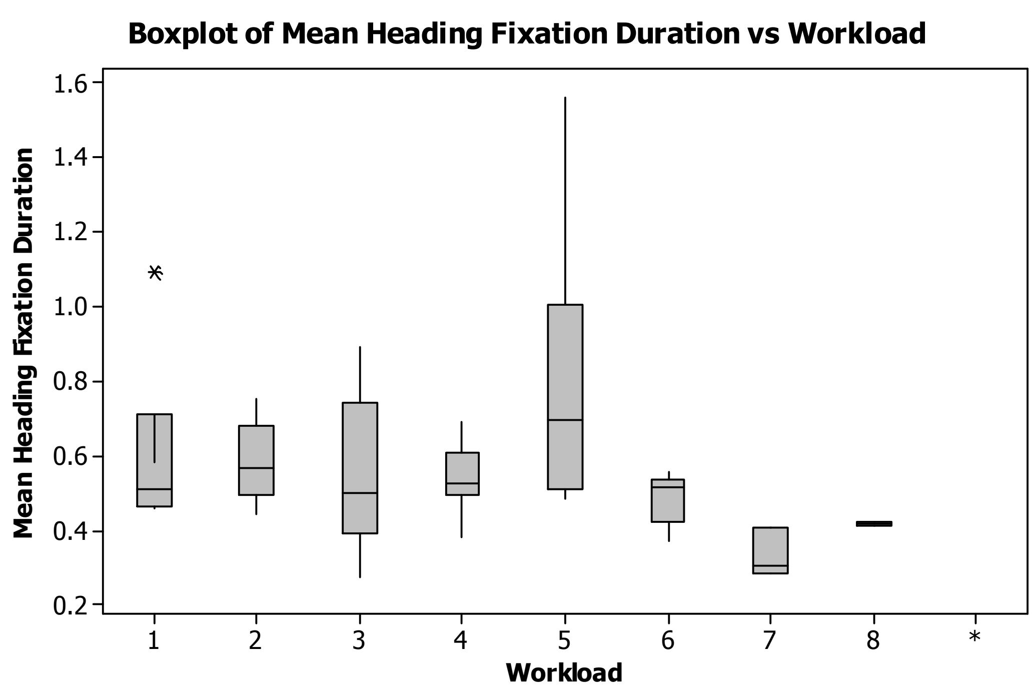


Figure A11. Mean Heading Fixation Duration vs. Workload Boxplot

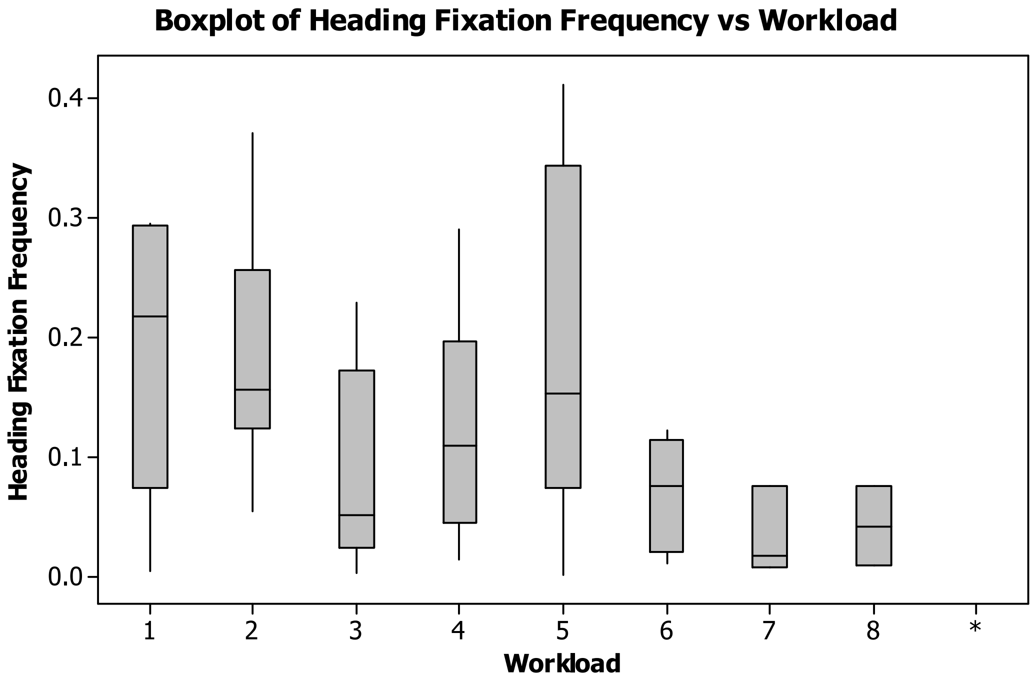


Figure A12. Heading Fixation Frequency vs. Workload Boxplot

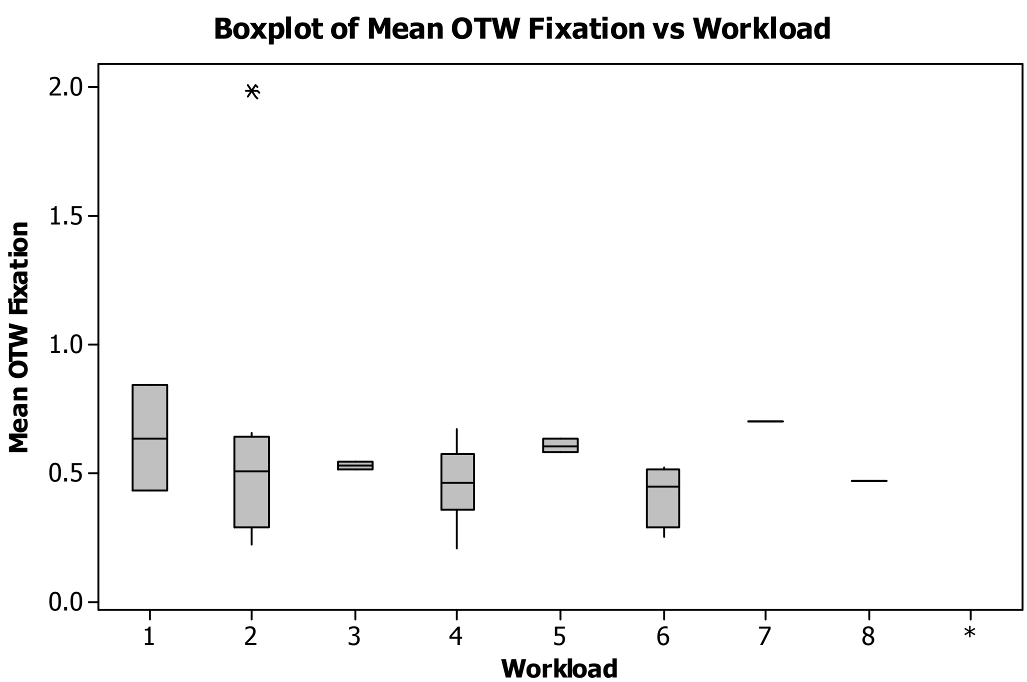


Figure A13. Mean OTW Fixation Duration vs. Workload Boxplot

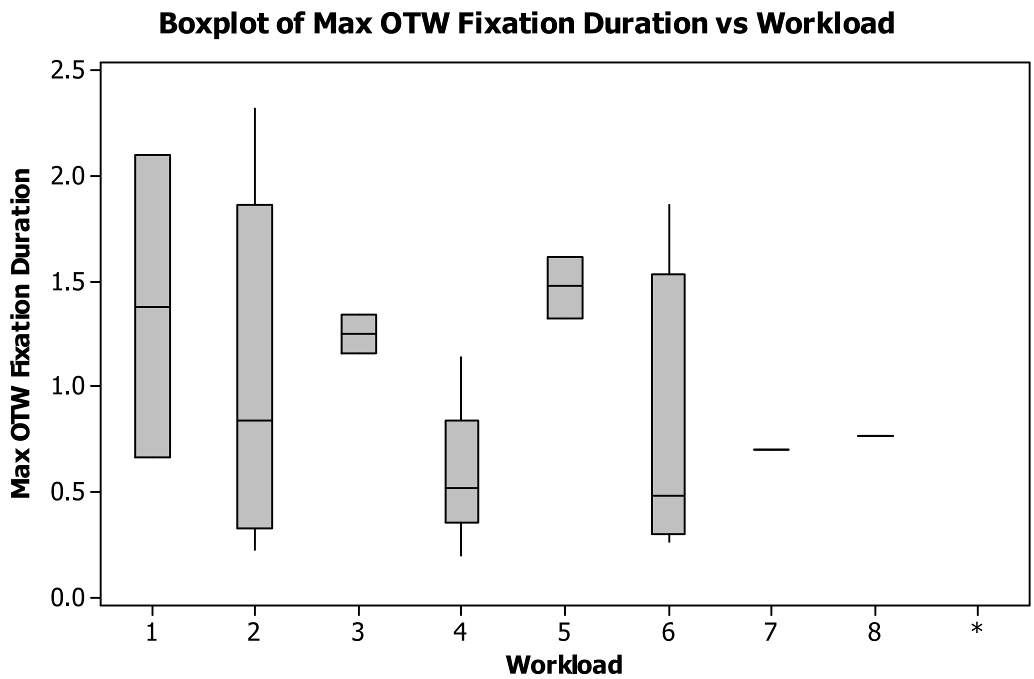


Figure A14. Max OTW Fixation Duration vs. Workload Boxplot

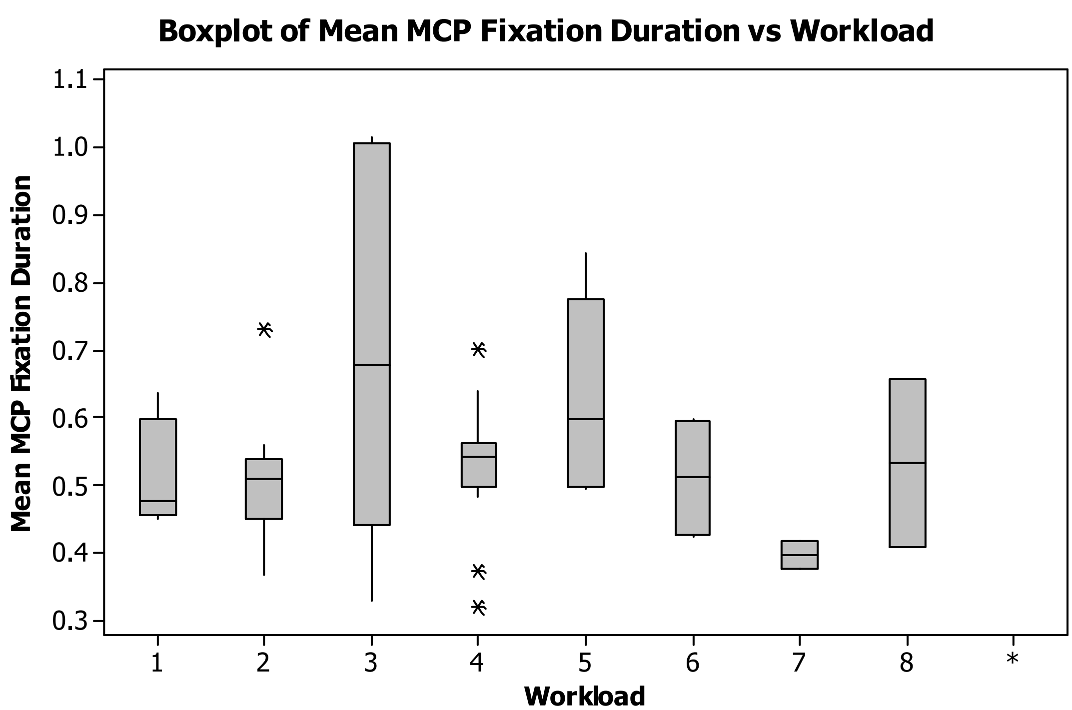


Figure A15. Mean MCP Fixation Duration vs. Workload Boxplot

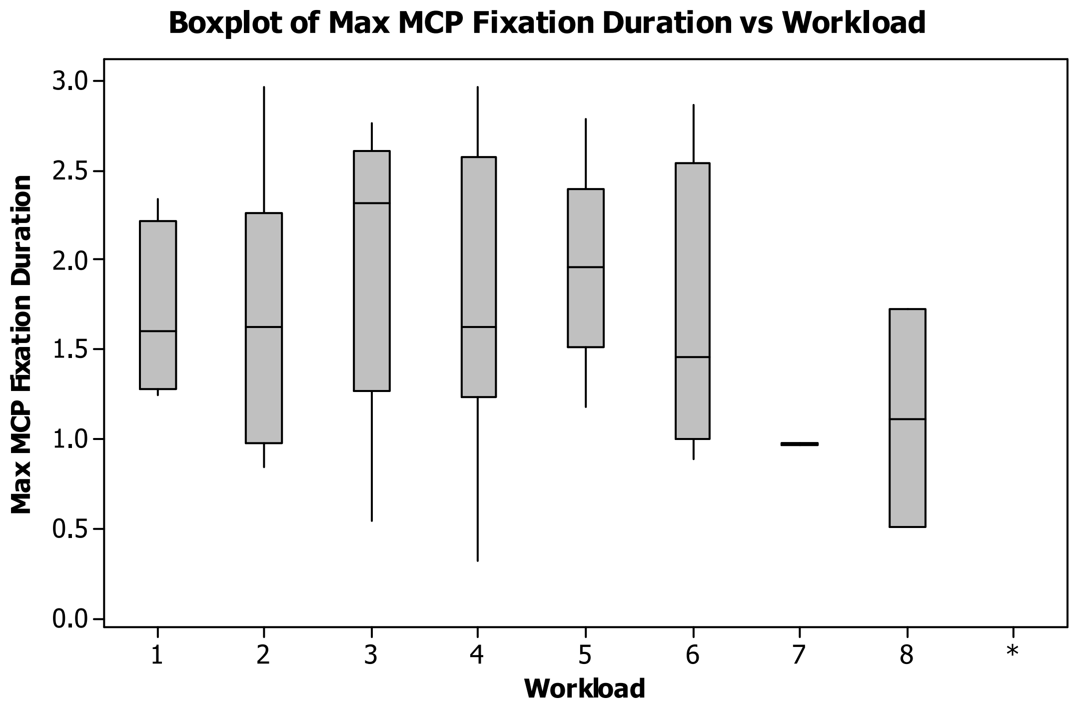


Figure A16. Max MCP Fixation Duration vs. Workload Boxplot

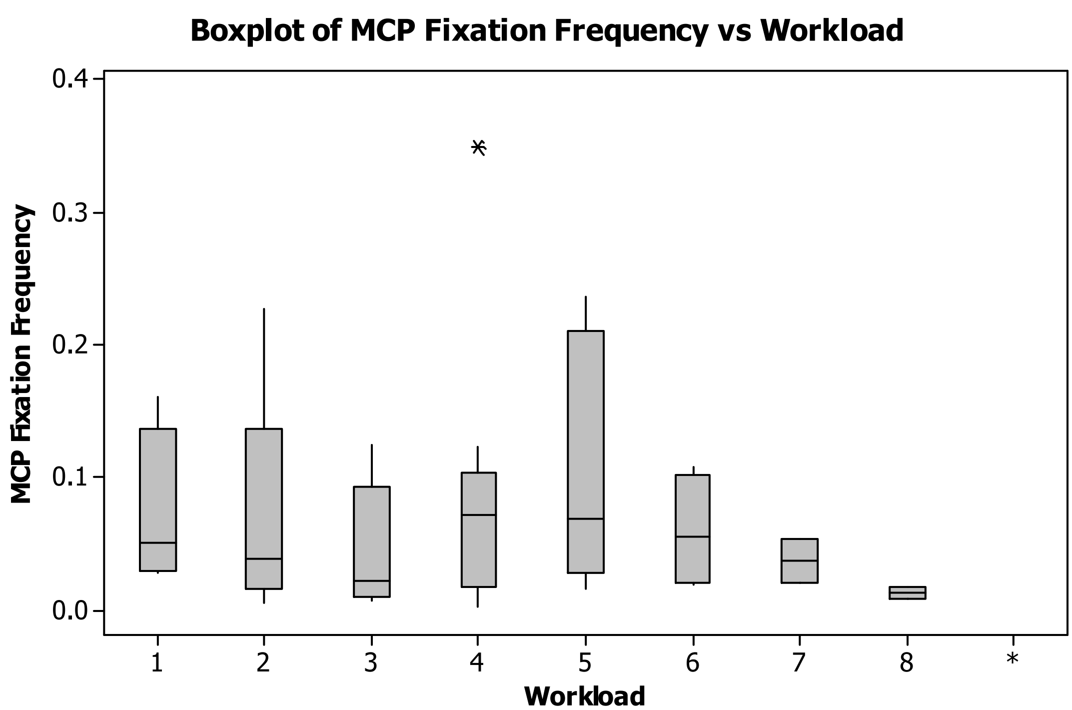


Figure A17. MCP Fixation Frequency vs. Workload Boxplot

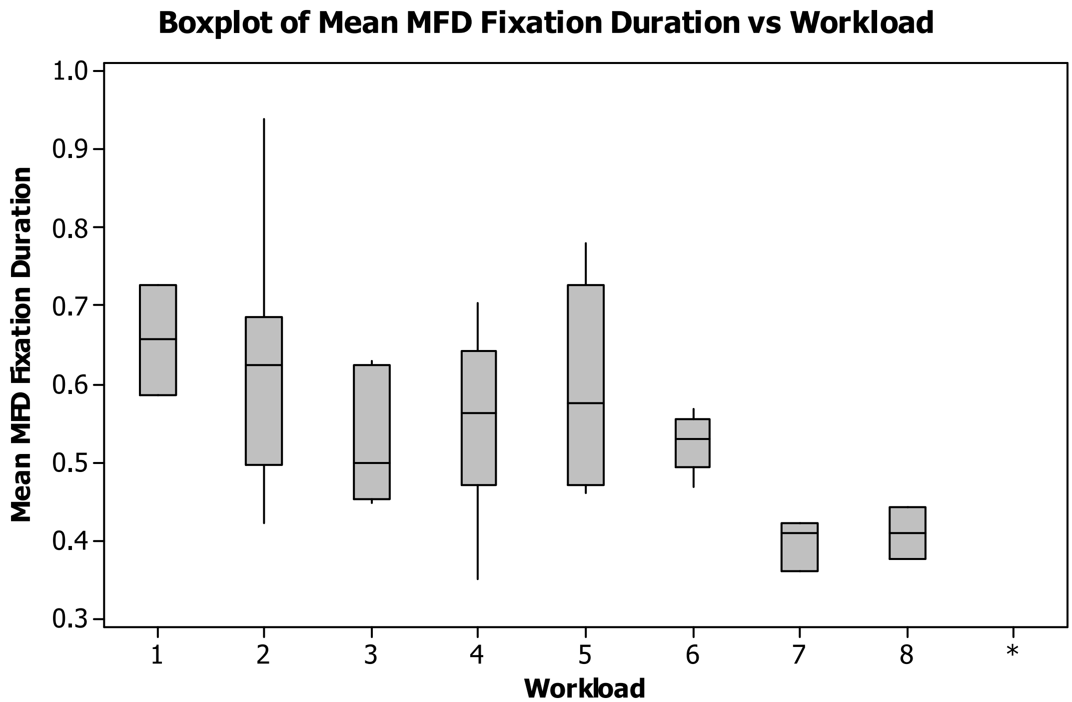


Figure A18. Mean MFD Fixation Duration vs. Workload Boxplot

Figure A19. Max MFD Fixation Duration vs. Workload Boxplot

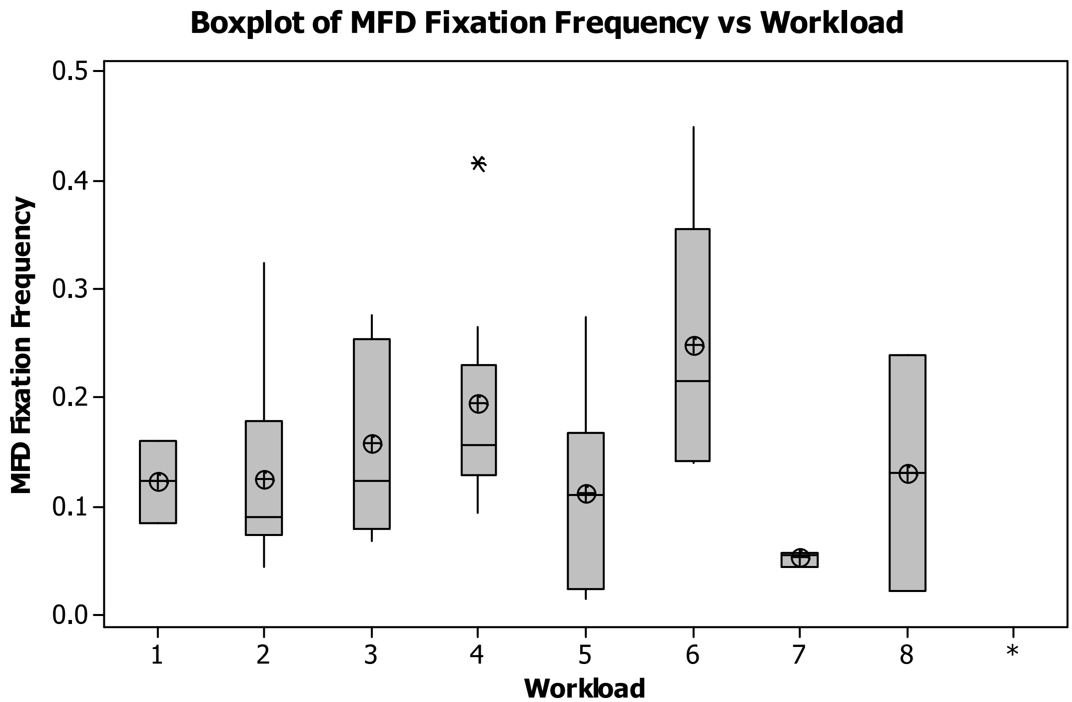


Figure A20. MFD Fixation Frequency vs. Workload Boxplot

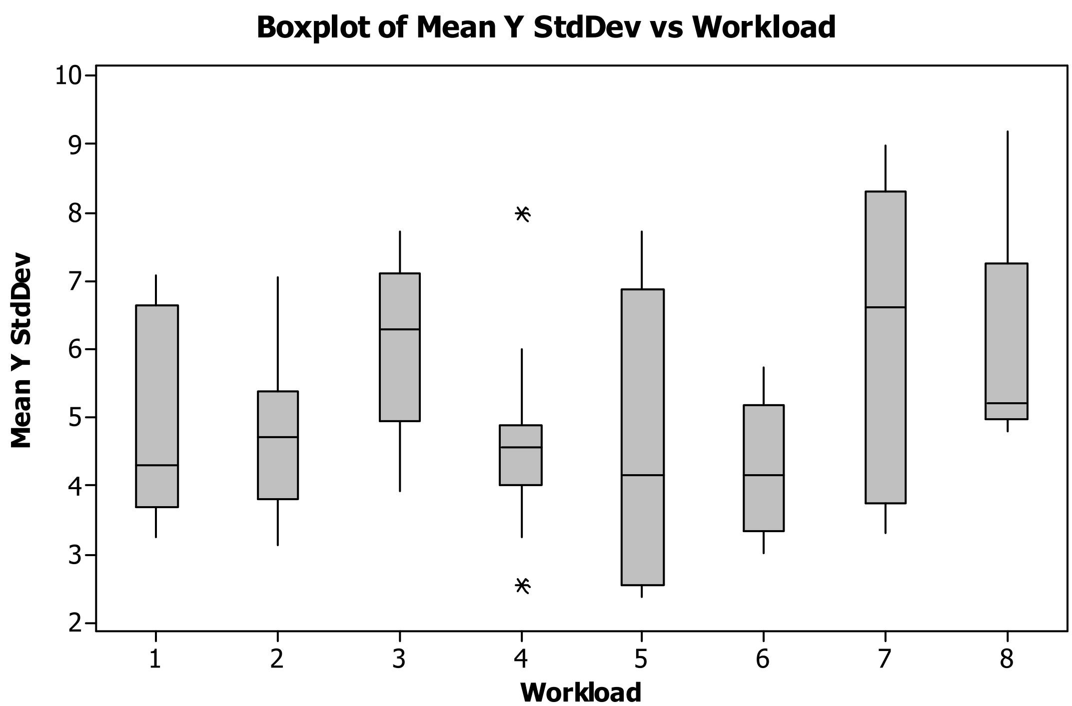


Figure A21. Mean Y StdDev vs. Workload Boxplot

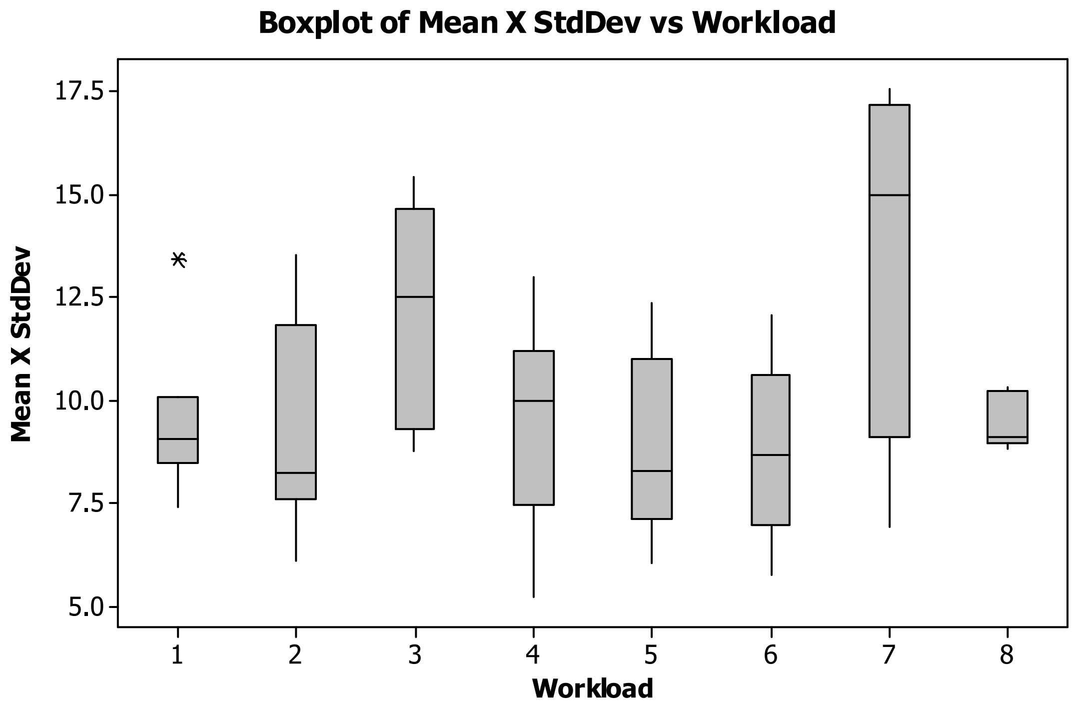


Figure A22. Mean X StdDev vs Workload Boxplot

```
The regression equation is
AVERAGE BEDFORD = 1.28 + 0.116 NASA-TLX Total

Predictor             Coef   SE Coef      T      P
Constant            1.2817    0.2489   5.15  0.000
NASA-TLX Total    0.115729  0.008985  12.88  0.000


S = 1.07239   R-Sq = 69.2%   R-Sq(adj) = 68.7%


Analysis of Variance

Source          DF      SS      MS       F      P
Regression       1  190.81  190.81  165.92  0.000
Residual Error  74   85.10    1.15
Total           75  275.91
```

Figure A23. NASA-TLX vs. Bedford Regression

```
The regression equation is
AVERAGE BEDFORD = 7.49 - 0.131 SART SCORE


Predictor        Coef   SE Coef      T      P
Constant       7.4856    0.6134  12.20  0.000
SART SCORE   -0.13121   0.02248  -5.84  0.000


S = 1.59785   R-Sq = 31.5%   R-Sq(adj) = 30.6%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       1   86.978  86.978  34.07  0.000
Residual Error  74  188.932   2.553
Total           75  275.910
```

Figure A24. SART vs. Bedford Regression

General Linear Model: Workload versus Subject, Mean Fixation Du, ...

Factor	Type	Levels	Values
Subject	random	12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12

Analysis of Variance for Workload, using Adjusted SS for Tests

Source	Model DF	Reduced DF	Seq SS
Subject	11	11	196.2004
Mean Fixation Duration	76	58+	109.7476
Subject*Mean Fixation Duration	836	0+	0.0000
Max Fixation Duration	41	0+	0.0000
Subject*Max Fixation Duration	451	0+	0.0000
Fixation Frequency	76	0+	0.0000
Subject*Fixation Frequency	836	0+	0.0000
Mean Saccade Length	76	0+	0.0000
Subject*Mean Saccade Length	836	0+	0.0000
Max Saccade Length	76	0+	0.0000
Subject*Max Saccade Length	836	0+	0.0000
Error	-4075	7	10.0000
Total	76	76	315.9481

+ Rank deficiency due to empty cells, unbalanced nesting, collinearity, or an undeclared covariate. No storage of results or further analysis will be done.

S = 1.19523   R-Sq = 96.83%   R-Sq(adj) = 65.64%

Figure A25. Global Composite Metric Repeated Measures ANOVA

Regression Analysis: Workload versus Mean Fixatio, Max Fixation, ...

```
The regression equation is
Workload = 6.23
           + 12.0 Mean Fixation Duration
           - 0.061 Max Fixation Duration
           + 0.41 Fixation Frequency
           - 0.021 Mean Saccade Length
           + 0.0210 Max Saccade Length
           - 8.33 Mean Altitude Fixation Duration
           + 0.38 Max Altitude Fixation Duration
           + 0.0953 Altitude Fixation Frequency
           - 1.81 Mean Heading Fixation Duration
           - 0.871 Max Heading Fixation Duration
           - 0.00245 Heading Fixation Frequency
           - 3.39 Mean MFD Fixation Duration
           - 2.48 Max MFD Fixation Duration
           + 8.13 MFD Fixation Frequency
           - 2.05 Mean MCP Fixation Duration
           + 1.49 Max MCP Fixation Duration
```

Predictor	Coef	SE Coef	T	P
Constant	6.233	3.623	1.72	0.109
Mean Fixation Duration	11.98	13.88	0.86	0.404
Max Fixation Duration	-0.0608	0.6174	-0.10	0.923
Fixation Frequency	0.411	1.423	0.29	0.777
Mean Saccade Length	-0.0209	0.1130	-0.18	0.856
Max Saccade Length	0.02097	0.01934	1.08	0.298
Mean Altitude Fixation Duration	-8.326	7.021	-1.19	0.257
Max Altitude Fixation Duration	0.375	1.024	0.37	0.720
Altitude Fixation Frequency	0.09534	0.06589	1.45	0.172
Mean Heading Fixation Duration	-1.805	4.336	-0.42	0.684
Max Heading Fixation Duration	-0.8708	0.7037	-1.24	0.238
Heading Fixation Frequency	-0.002448	0.007714	-0.32	0.756
Mean MFD Fixation Duration	-3.389	5.538	-0.61	0.551
Max MFD Fixation Duration	-2.4792	0.8313	-2.98	0.011
MFD Fixation Frequency	8.135	3.847	2.11	0.054
Mean MCP Fixation Duration	-2.049	3.492	-0.59	0.567
Max MCP Fixation Duration	1.4854	0.7349	2.02	0.064

S = 1.11789   R-Sq = 73.7%   R-Sq(adj) = 41.4%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	16	45.621	2.851	2.28	0.070
Residual Error	13	16.246	1.250		
Total	29	61.867			

Figure A26. ET Metric vs. Workload Regression

Repeated Measures ANOVA -

General Linear Model: Workload versus Subject, Mean Fixation Du, ...

Factor	Type	Levels	Values
Subject	random	12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12

Analysis of Variance for Workload, using Adjusted SS for Tests

Source	Model DF	Reduced DF	Seq SS
Subject	11	11	196.2004
Mean Fixation Duration	76	58+	109.7476
Subject*Mean Fixation Duration	836	0+	0.0000
Max Fixation Duration	41	0+	0.0000
Subject*Max Fixation Duration	451	0+	0.0000
Fixation Frequency	76	0+	0.0000
Subject*Fixation Frequency	836	0+	0.0000
Mean Saccade Length	76	0+	0.0000
Subject*Mean Saccade Length	836	0+	0.0000
Max Saccade Length	76	0+	0.0000
Subject*Max Saccade Length	836	0+	0.0000
Error	-4075	7	10.0000
Total	76	76	315.9481

+ Rank deficiency due to empty cells, unbalanced nesting, collinearity, or an undeclared covariate. No storage of results or further analysis will be done.

S = 1.19523   R-Sq = 96.83%   R-Sq(adj) = 65.64%

Figure A27. ET Metrics vs. Workload Repeated Measures ANOVA

Regression Analysis: Workload versus Mean Fixatio, Max Fixation, ...

```
The regression equation is
Workload = 7.69 + 11.9 Mean Fixation Duration - 0.134 Max Fixation Duration
           - 0.54 Fixation Frequency - 0.050 Mean Saccade Length
           + 0.0211 Max Saccade Length - 7.49 Mean Altitude Fixation Duration
           + 0.075 Max Altitude Fixation Duration
           + 0.0962 Altitude Fixation Frequency
           - 2.71 Mean Heading Fixation Duration
           - 0.509 Max Heading Fixation Duration
           - 3.38 Mean MFD Fixation Duration - 2.09 Max MFD Fixation Duration
           + 6.63 MFD Fixation Frequency - 1.89 Mean MCP Fixation Duration
           + 1.31 Max MCP Fixation Duration - 0.681 F/D Bi - 0.133 Autopilot Bi


30 cases used, 54 cases contain missing values
```

Predictor	Coef	SE Coef	T	P
Constant	7.688	3.393	2.27	0.043
Mean Fixation Duration	11.88	12.72	0.93	0.369
Max Fixation Duration	-0.1342	0.6100	-0.22	0.830
Fixation Frequency	-0.541	1.672	-0.32	0.752
Mean Saccade Length	-0.0500	0.1180	-0.42	0.679
Max Saccade Length	0.02111	0.01878	1.12	0.283
Mean Altitude Fixation Duration	-7.488	7.171	-1.04	0.317
Max Altitude Fixation Duration	0.0753	0.7384	0.10	0.921
Altitude Fixation Frequency	0.09616	0.05858	1.64	0.127
Mean Heading Fixation Duration	-2.714	2.002	-1.36	0.200
Max Heading Fixation Duration	-0.5086	0.8306	-0.61	0.552
Mean MFD Fixation Duration	-3.385	5.682	-0.60	0.562
Max MFD Fixation Duration	-2.0925	0.9587	-2.18	0.050
MFD Fixation Frequency	6.629	4.236	1.57	0.144
Mean MCP Fixation Duration	-1.889	3.397	-0.56	0.588
Max MCP Fixation Duration	1.3123	0.7234	1.81	0.095
F/D Bi	-0.6811	0.9011	-0.76	0.464
Autopilot Bi	-0.1328	0.6815	-0.19	0.849

```
S = 1.12717   R-Sq = 75.4%   R-Sq(adj) = 40.4%


Analysis of Variance
```

Source	DF	SS	MS	F	P
Regression	17	46.620	2.742	2.16	0.090
Residual Error	12	15.246	1.271		
Total	29	61.867			

Figure A28. Task + ET Metrics vs. Workload Regression

General Linear Model: Workload versus Subject, Mean Fixation Du, ...

Factor	Type	Levels	Values
Subject	random	12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
F/D Bi	fixed	2	0, 1
Autopilot Bi	fixed	2	0, 1

Analysis of Variance for Workload, using Adjusted SS for Tests

Source	Model DF	Reduced DF	Seq SS
Subject	11	11	196.2004
Mean Fixation Duration	76	58+	109.7476
Subject*Mean Fixation Duration	836	0+	0.0000
Max Fixation Duration	41	0+	0.0000
Subject*Max Fixation Duration	451	0+	0.0000
Fixation Frequency	76	0+	0.0000
Subject*Fixation Frequency	836	0+	0.0000
Mean Saccade Length	76	0+	0.0000
Subject*Mean Saccade Length	836	0+	0.0000
Max Saccade Length	76	0+	0.0000
Subject*Max Saccade Length	836	0+	0.0000
F/D Bi	1	1	0.7000
Subject*F/D Bi	11	0+	0.0000
Autopilot Bi	1	1	4.8000
Subject*Autopilot Bi	11	0+	0.0000
Error	-4099	5	4.5000
Total	76	76	315.9481

+ Rank deficiency due to empty cells, unbalanced nesting, collinearity, or an undeclared covariate. No storage of results or further analysis will be done.

S = 0.948683   R-Sq = 98.58%   R-Sq(adj) = 78.35%

Figure A29. Task + ET Metrics vs. Workload Repeated Measures ANOVA

Repeated Measures ANOVA – Task against Workload
General Linear Model: Workload versus Subject, F/D, Autopilot

Factor	Type	Levels	Values
Subject	random	12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
F/D	fixed	2	OFF, ON
Autopilot	fixed	2	OFF, ON

Analysis of Variance for Workload, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Subject	11	217.274	149.008	13.546	7.07	0.014 x
F/D	1	19.201	4.083	4.083	3.77	0.078
Subject*F/D	11	13.385	11.917	1.083	0.83	0.612
Autopilot	1	9.025	9.025	9.025	4.14	0.067
Subject*Autopilot	11	24.008	24.008	2.183	1.67	0.109
Error	48	62.667	62.667	1.306		
Total	83	345.560				

x Not an exact F-test.

S = 1.14261   R-Sq = 81.87%   R-Sq(adj) = 68.64%

Figure A30. Task (including land decision) vs. Workload ANOVA

Repeated Measures ANOVA – Task against Workload

General Linear Model: Workload versus Subject, F/D, ...

Factor	Type	Levels	Values
Subject	random	12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
F/D	fixed	2	OFF, ON
Autopilot	fixed	2	OFF, ON
Land or Go Around	fixed	3	Engine Failure, GO AROUND, LAND

Analysis of Variance for Workload, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P	
Subject	11	217.274	129.694	11.790	282.97	0.989	x
F/D	1	19.201	4.083	4.083	3.77	0.078	
Subject*F/D	11	13.385	11.917	1.083	0.53	0.863	
Autopilot	1	9.025	12.000	12.000	5.87	0.034	
Subject*Autopilot	11	24.008	22.500	2.045	1.00	0.473	
Land or Go Around	2	3.250	3.250	1.625	3.43	0.050	
Subject*Land or Go Around	22	10.417	10.417	0.473	0.23	0.999	
Error	24	49.000	49.000	2.042			
Total	83	345.560					

x Not an exact F-test.

S = 1.42887   R-Sq = 85.82%   R-Sq(adj) = 50.96%

Figure A31. Task (incl. land decision) vs. Workload Repeated Measures ANOVA

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