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THESIS

USING MODELING TO PREDICT THE EFFECTS OF AUTOMATION ON MEDEVAC PILOT COGNITIVE WORKLOAD

by

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13. ABSTRACT (maximum 200 words)

The Holistic Situational Awareness - Decision Making (HSA-DM) program is researching ways to aid pilots via avionics essential to the Future Vertical Lift (FVL) rotor-wing platform. As pilots manage the new avionics that FVL will bring to the battlefield, automation assistance will be essential.

This study's goal is to determine to what extent automation reduces pilot cognitive workload particularly when performing communication tasks. The quantitative analysis is based on cognitive walkthroughs with active-duty helicopter pilots. Pilot interviews were also conducted to assess how tasks are completed, and more importantly, to ascertain the cognitive workload associated with those tasks. This information is implemented into computer models of a routine helicopter flight to accurately predict pilot workload during a mission. These models also predict which tasks would add the most value to pilots and FVL if automated mission tasks were implemented.

The research indicates that by automating communication tasks for the pilot and copilot, workload is reduced to an optimal level. Based on these findings, monitor radio nets, adjust volume, input channel, select channel, and send JVMF messages should be automated. In addition, this analysis establishes a cost-effective, valid, and repeatable framework for future workload studies on automated tasks in FVL.

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LIST OF ACRONYMS AND ABBREVIATIONS

AI	Artificial Intelligence
AFC	Army Futures Command
ANOVA	Analysis of Variance
ARI	Army Research Institute
ATM	Aircrew Training Manual
BFT	Blue Force Tracker
CDM	Critical Decision Method
CW	Cognitive Workload
DEVCOM	Army Development Command
FARA	Future Attack Reconnaissance Aircraft
FVL	Future Vertical Lift
HCI	Human-Computer Interaction
HSA-DM	Holistic Situational Awareness-Decision Making
HITL	Human-In-The-Loop
IMPRINT	Improved Performance Research Integration Tool
IRB	Institutional Review Board
JVMF	Joint Variable Message Format
MEDEVAC	Medical Evacuation
MRT	Multiple Resource Theory
NASA	National Aeronautics and Space Administration
NPS	Naval Postgraduate School
OCV	Optimally Crewed Vehicle
SME	Subject Matter Expert
TAWL	Task Analysis Workload
VACP	Visual, Auditory, Cognitive, and Psychomotor

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EXECUTIVE SUMMARY

PROJECT SUMMARY

The purpose of this research was to provide recommendations of which communications tasks should be automated to reduce Future Vertical Lift (FVL) aircrew cognitive workload during a medical evacuation (MEDEVAC) scenario. The goal of this project is to inform future HSA-DM design decisions on task automation. To accomplish this goal, we began with a literature review to increase our understanding of cognitive workload and the methods that have been used to measure and model this workload. This research led us to the Improved Performance Research Integration Tool (IMPRINT), which is the tool we used to conduct our analysis. We also researched how automation has been used to mitigate workload and how pilots communicate in-flight. We then conducted a task analysis by leveraging the UH-60 Aircrew Training Manual (ATM) and cognitive walkthroughs and interviews with pilots to identify the critical tasks required to operate a UH-60 in a MEDEVAC scenario. Next, we developed a model in IMPRINT using the data gathered from our task analysis to realistically replicate the "enroute" phase of flight. We analyzed the results of this model to identify which communication tasks contributed most to cognitive overload. Finally, we modified the model multiple times to investigate how automating the selected communication tasks impacted cognitive workload. Analyzing the results of these modified models allowed us to develop recommendations for communication task automation and future research.

BACKGROUND

Through the FVL program, the Army seeks to develop aviation technology and capacity, building new platforms and operational concepts (Department of the Army 2019). The Army will use automation and artificial intelligence (AI) to increase aircraft capabilities (Department of the Army n.d.). The Future Vertical Lift program needs AI and automation to keep up with an increasingly sophisticated battlespace. Their engineers will automate pilot activities to lessen cognitive effort. Our study concentrated on aircrew and technical system communications during a MEDEVAC flight on an FVL platform. Pilots must monitor the aircraft's systems, stay vigilant to danger, locate prospective targets, and communicate with their aircrew, other aircraft, and ground personnel. Automation may help pilots with these tasks, but they must carefully monitor the automated systems.

FINDINGS AND CONCLUSIONS

Through our research approach, we identified six communication tasks that contributed most to cognitive overload:

- Monitor radio nets (pilot)
- Monitor radio nets (copilot)
- Input channel
- Select channel
- Send JVMF message
- Adjust volume

Automating these tasks lowered pilot cognitive overload by 55.9%, copilot cognitive overload by 14.4%, and overall cognitive overload by 28%. The crew workload difference between the two models is statistically significant, as reflected in an ANOVA analysis.

Because the UH-60 ATM emphasized internal communications, the pilot and copilot maintain control of those tasks. Additionally, our research emphasized that the copilot should maintain the ability to freely transmit externally and take notes as needed. Finally, by analyzing individual model runs, we found that workload fluctuations are random and have a great deal to do with the degree or multitasking being conducted by either the pilot or copilot

RECOMMENDATIONS FOR FUTURE RESEARCH

The project's findings show that the IMPRINT model may be used to simulate various tasks and report cognitive workload for individual crewmembers. Data from six

MEDEVAC pilots produced the required results. Our first recommendation is to conduct interviews with more MEDEVAC pilots to provide a larger sample size to develop more accurate cognitive workload values for the model. Based on this additional data, further analysis is needed on how to accomplish the recommended automated tasks using current or future technology.

Our second recommendation is to further develop the IMPRINT model to analyze more scenarios, such as the remaining MEDEVAC flight, environmental hazards, and night flying. Other crew members beyond the pilot and copilot should be included.

Our third recommendation is to validate this data in a virtual simulation platform. This validation would allow researchers to test and assess the new automated mechanics. This information will yield information IMPRINT cannot, such as operator confidence in automation and pilot fatigue. As automation solutions are developed, we advocate doing cost-benefit analyses to assess whether automating certain tasks are worth the investment.

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I. INTRODUCTION

A. BACKGROUND

The Future Vertical Lift (FVL) program is an Army initiative designed to develop the next generation of aerial platforms (Department of the Army 2019). Through this program, the Army plans to significantly advance aviation technology and capability, building the new platforms and operational concepts required to function in an increasingly contested and difficult battlespace (Department of the Army 2019). In particular, the Army will seek to integrate technological improvements such as automation and artificial intelligence (AI), to enhance aviation capabilities (Department of the Army n.d.). AI and Automation are necessary in FVL aircraft to cope with the demands of an increasingly technological battlespace. The FVL program expects to reduce pilot cognitive workload by automating the most appropriate pilot tasks. For the purposes of our research, we will focus on the communications activities among aircrew members and technological systems during a medical evacuation (MEDEVAC) mission on a FVL platform.

Careful consideration of the human component is required to design effective human-automation systems (Ernst et al. 2020). According to Ernst (2020), Army officials seek to facilitate "cognitive offloading while employing human crew intuition and situational curiosity to take advantage of leverage points in the battlespace" (8). Aircraft designers and aeronautical engineers often create complex software to assist pilots with managing aircraft systems. These advances in avionics come with a cost: the cognitive workload frequently increases for both the pilot in command and the copilot (Ernst et al. 2020). Pilots must fly the aircraft while monitoring the aircraft's systems, being alert to any danger, seeking possible targets, and communicating with their aircrew members, other aircraft, and ground elements. The critical nature of MEDEVAC missions requires pilots to fly their aircraft at night and in various weather conditions. Automation can aid pilots in completing these duties; however, the automated systems must be closely monitored by pilots.

Research is needed to understand the impact of introducing AI into FVL platforms on pilot and copilot cognitive workload. In December 2021, a Naval Postgraduate School (NPS) capstone team composed mainly of pilots began researching the cognitive workload of pilots and the factors that increase their workload (Carter et al. 2021). The goal of their research was to inform the Holistic Situational Awareness-Decision Making (HSA-DM) project team of those factors that contribute most to cognitive workload. This information helped determine which specific tasks should be automated and if that automation would reduce or possibly increase pilot workload (Carter et al. 2021). Carter et al. used qualitative interview methods and an influence diagram to conduct the study. Their results identified the factors that contribute most to cognitive workload: flight profile, primary task complexity, and light factors. These factors had a more significant impact on cognitive workload in a complex scenario when compared to a simple scenario. During a recent visit to NPS, the HSA-DM project director recommended future research focus on the cognitive workload associated with communication tasks. In the report by Carter et al. (2021), one of the recommendations for future research was to conduct a task analysis to identify which tasks contribute most to high workload. The report further suggested developing a model to evaluate the impacts that automating those tasks would have on pilot workload.

That is where we, as a capstone team, pick up the mantle. The focus of our research is modeling the communications between the two aircrew members and the envisioned AI system in an effort to determine whether the cognitive workload is appropriately distributed among the human and AI team members on board the FVL platforms.

B. PROBLEM STATEMENT

The research by Carter et al. inspired us to investigate cognitive workload associated with communication tasks in a MEDEVAC scenario. We will use modelling and simulation to investigate how communication tasks can be distributed between the pilot, copilot, and envisioned AI system to mitigate MEDEVAC pilot workload.

C. RESEARCH QUESTIONS

Our overarching research question is as follows: To what extent is a pilot's cognitive workload reduced if communication tasks are automated? To address this question effectively, numerous sub-questions emerge:

- How can communication tasks be distributed between pilot, copilot, and the envisioned AI system?
- How does workload vary over the course of a particular phase of a MEDEVAC mission?

D. STAKEHOLDERS

Table 1 describes the major stakeholders relative to this research effort. The HSA-DM project team is part of The U.S. Army Combat Capabilities Development Command (DEVCOM) Aviation and Missile Center and is a subsection of Army Futures Command (AFC). One of AFC's missions is to research and develop new weapons systems for aircraft, missiles, and unmanned vehicles, providing one-stop technical support capability for these systems throughout their life cycles. Shivers and Morony (2021) detail several goals for the FVL program:

1. "Provide optimized task loading for Future Vertical Lift /aviation warfighters (pilots, copilots) by developing cognitive workload management capabilities" (13).
2. "Improve combat mission performance of Novice, Busy, Fatigued, and Injured pilots by delivering decision aiding algorithms, improved human-machine interface hardware/software, and implementing autonomous flight controls" (13).
3. "Develop products based on Modular Open Systems Approach (MOSA) principles and aligned with the FVL Architecture Framework utilizing Model-Based Systems Engineering" (13).

Accordingly, the HSA-DM project team needs a cognitive workload prediction model to determine FVL task automation requirements. Providing these results through the Improved Performance Research Integration Tool (IMPRINT) model is the primary purpose of this project.

Pilots are project stakeholders because they are accountable for ensuring the safe and successful functioning of FVL platforms. Their purpose in the scope of this research is to minimize cognitive overload. This target will be met through optimizing FVL pilot workload management by automating certain tasks and enabling them to focus on tasks that demand expert knowledge, competence, and assessment.

Table 1. Stakeholder Analysis

Stakeholder	Need	Role	Goal
HSA-DM Project Team (CCDC AvMC)	Cognitive workload prediction model	Sponsor	Determine FVL task automation requirements
Army Helicopter Pilots	Optimized cognitive workload	Operator	Minimize cognitive overload

E. SCOPE

The goal of this project is to inform future HSA-DM design decisions on task automation. The HSA-DM team has identified seven operational context vignettes for their project team to consider (Shivers n.d.). This research project will use the MEDEVAC vignette for model verification, with emphasis on communication tasks. This project intends to develop a model that provides insight into the cognitive workload of MEDEVAC pilots. The tool used to develop this model is IMPRINT. The scope of this project is limited to task analysis and IMPRINT model development and verification within the specific mission scenario. The portion of the MEDEVAC flight modeled begins after takeoff to an objective and ends before entering the hover sequence.

F. PROJECT OVERVIEW

We developed an IMPRINT model for a MEDEVAC mission. The model represents pilot tasks and is separated into aviate, navigate, and communication tasks to generate an understanding of what subtasks would be most beneficial if automated. This research is aligned with the HSA-DM focus area of supervised autonomy of select tasks (Shivers 2021).

We start with a literature review, in which we present previous research on cognitive workload (CW), measures and models of workload, and the application of those models in human-automation teaming. While there are many modeling techniques for CW, we utilized IMPRINT. The IMPRINT modeling tool has been used extensively since the 1990s, when it was developed by the Army Research Laboratory. IMPRINT has been previously used to model aspects of human behavior such as "task analysis, workload modeling, embedded personnel characteristics data, and performance-shaping and degradation functions and stressors" (Salvi 2001, 2). Before the IMPRINT model was built, we established MEDEVAC pilot tasks and conducted a task analysis. The task analysis consists of 1) identifying pilot tasks that must be completed throughout the mission, and 2) developing a graphical depiction of those tasks and their subjective workload values (Bierbaum, Szabo, and Aldrich 1988). The task analysis assists the research team in organizing pilot tasks into smaller segments and functions to allow workload variables and values to be applied. This analysis aids in the development and organization of our IMPRINT model and provides an opportunity to validate our assumptions throughout critical steps in our timeline.

Once the IMPRINT model was complete, we demonstrated our results and consulted MEDEVAC pilots at NPS for validation of the model and model outputs. We refined our results based on the feedback from the pilots and completed the final chapters of this paper. This outcome ensures that all meaningful data are reported to our project stakeholders.

G. BENEFIT OF STUDY

Two major benefits result from our research into specific vignettes of automated tasks for both the pilot and copilot. First, the research will provide the HSA-DM team a model that will include quantitative data on the pilot tasks that lend themselves to be automated. Second, FVL pilots will be able to apply our analytical data to the FVL platforms so that their cognitive workload is greatly reduced during MEDEVAC missions.

The first benefit will provide analytical and quantitative data through IMPRINT that shows how a pilot's cognitive workload is reduced when specific tasks are automated. The IMPRINT models used during our research will show the pilot's cognitive workload during medical evacuation missions, specifically with communication automation. The model will also reveal the increased or decreased cognitive workload associated with communication tasks. The simulations through the designed IMPRINT models will assist in determining if the tasks are worth automating.

The second benefit is the data needed to continue future research within the FVL program. This research will allow the HSA-DM team to understand which tasks make sense to automate and to run those tasks through pilot simulators. Quantitative data will inform which tasks are worth automating. Likewise, pilots will be able to select which tasks they wish to be automated for a flight based on experience-based preferences.

Overall, this study will inform the FVL community, specifically the HSA-DM team, as they develop an understanding of where AI can be leveraged to assist human teams in flying. Next, we will discuss the relevant research that we used to develop our project methodology.

II. LITERATURE REVIEW

A. INTRODUCTION

The research team established a hierarchy of the collected research by theory, concepts, indicators, variables, and values (Walliman 2010). The research team developed inclusion and exclusion criteria as well as keywords to aid in tailoring the search to those sources most relevant to the research problem.

The research team used a variety of databases including the Dudley Knox Library, Google Scholar, and Defense Technical Information Center (DTIC) to locate articles covering the topic areas. Key words and phrases used by the team during research included "cognitive workload," "future vertical lift," "cognitive load measurement," "human performance modeling," and "improved performance research integration tool." Criteria for disqualification included any literature that was not written in English, was not freely available, or potentially biased articles. The inclusion criteria used by the team comprised the following: the literature had to be from a scholarly source, peer-reviewed, and provided information that supported our research criteria.

The team used this process to locate and analyze key literature to establish background understanding and the concepts relevant to the research problem. The first research category we focused on was cognitive workload: what it is, how it is measured, and how it can be modeled. We then investigated how this information could be used to inform designs of future automation systems.

B. COGNITIVE WORKLOAD

In order to appreciate how pilots are affected by flight tasks and how automation could affect their flight performance, we needed to understand cognitive workload as a concept. This includes how humans manage their workload and how researchers measure workload.

Cognitive Workload (CW) is a phenomenon that all humans experience and manage daily and has been researched extensively since the mid-20th century. As systems and machines increase in complexity, we see that humans often are the most limiting factor in these systems. This is because they require a significant cognitive workload to operate and manage systems as to automation (Chen et al. 2016).

The definitions of cognitive workload seen in the literature are very similar. These definitions all address the idea that workload is a finite resource managed by human operators during their task(s):

- Kantowitz (2000) defines mental workload as an "intervening variable, similar to attention, that modulates the tuning between the demands of the environment and the capacity of the [operator]" (3-457).

- NASA (2020) describes cognitive workload as the amount of effort people must exert to mentally use a machine interface.

- In "Workload Measures," Gawron (2019) describes workload as a "set of task demands, as effort, and as activity or accomplishment (3).

- Young et al. (2007) tells us that workload is the "level of attentional resources required to meet both objective and subjective criteria, which may be mediated by task demands, external support, and past experience" (21).

- Moray (1979) in "Mental Workload: Theory and Measurement" defines workload as "an inferred construct that mediates between task difficulty, operator skill, and observed performance" (13).

The body of research largely agrees on the internal and external variables which contribute to lower or higher rates of workload. Some of the factors seen in the definitions above are operator skill, the difficulty of the primary task, and environmental factors. Some additional variables explored in the literature are time pressure, working memory (Wickens

2017), “work ethic, emotional intelligence, anxiety, and conscientiousness” (Guastello 2015, 21). Gawron (2019) finds human stress response to be a significant factor as well.

A good example of workload is one the reader should have experienced: driving a car. Whenever we prepare to drive, especially in high-traffic or high-stress conditions, we feel the psychological effects of cognitive workload. The driver must maintain constant awareness of the car’s position in space relative to other cars and obstacles. They manage space between their car and other cars, listening to the radio, thinking about life’s distractions and what routes to take to the destination. When driving in difficult conditions, the driver must make split-second decisions while at very high speeds. They will feel a rise in heart rate and stress level the more quickly they must make a decision and the faster they are going. The situation described can become stressful very quickly, and that stressful feeling is that of high CW. The more tasks that happen at once, the greater the CW. As illustrated in Figure 1, the task performance quickly drops when mental workload is too high (Kantowitz 2000).

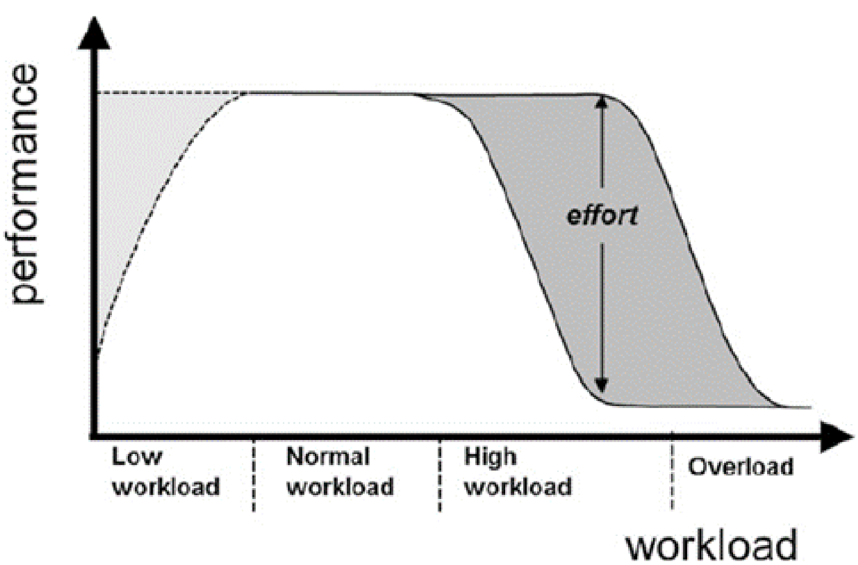


Figure 1. Performance as a Function of Workload Increases. Source: Chen et al. (2016).

The amount of CW that can be managed by an individual varies from person to person as a function of their domain knowledge, familiarity with the activity, amount of prior experience, and age (Chen et al. 2016). Workload is a finite resource, constrained by the operator's working memory. Once mental capacity has been maxed, task performance will decline as demands and fatigue increase (Gawron 2019). The negative effects of poor sleep and stress on performance are well established, and cognitive overload has similar consequences on task accomplishment (Wickens 2017).

In the driving analogy, when the driver reaches cognitive workload capacity, performance degradations manifest as swerving, missing a turn, or worse. When the limits of capacity are exceeded, operators will resist adding more tasks or changing tasks. This resistance, defined by Wickens (2000) as "switch bias," is driven by the need to make a trade-off decision between cognitive capacity and task performance (25). Kantowitz (2000) expands this idea, pointing out that workload suffers when the driver is at capacity but also when workload is too low, resulting in a lack of focus on the task. Stressed drivers or pilots will tend to choose between two options: making a higher-value choice or a lower-effort choice (Wickens 2017). The decision is made based on task outcome and the effect that choice will have on overall CW. Humans tend to want to stay in a lower effort state, sometimes inflating the importance of a decision to maintain steady-state effort (Wickens 2000). Therefore, special attention must be given to cognitive threshold and the effect that overload can have on decision making and performance. It is important to find ways to manage workload, reduce stress, and prevent over-tasking and to do this we must be able to accurately measure CW.

C. METHODS TO MEASURE COGNITIVE WORKLOAD

As technology continues to rapidly evolve, the demand for measuring cognitive workload continues to gain importance. The growing interest involves special emphasis on understanding human-computer interaction (HCI) and operator performance in situations where the work environment affords little room for human error. These types of working conditions require accuracy, mental focus, and quick-thinking skills that would normally apply to emergency response, aviation, incident management, and military command and control (Chen et al. 2016). Significant research has been conducted to measure cognitive workload to reduce human error and increase the safety of the operator. Methods for measuring CW range from simple questionnaires to more complex methods such as "functional brain imaging techniques" (Chen et al. 2016, 5). The four main methods used are as follows: subjective ratings, performance measures, physiological measures, and behavioral measures.

1. Subject Measures

Traditionally, researchers prefer to measure cognitive workload using subjective measures. Subjective ratings are usually accepted as the "ground truth" (Chen et al. 2016, 05). An example is asking users to provide detailed information using "introspection" as a form of self-assessment to determine how much mental capacity the operator exerted during the task (Chen et al. 2016). For the purposes of our research, we conducted interviews with pilots where they introspectively provided cognitive workload values for flight tasks. The information is then weighed against two types of scales: Unidimensional and multidimensional. Unidimensional measures the overall cognitive load and multidimensional focuses on the different components of load (Chen et al. 2016, 15). One method of multidimensional scale is the NASA Task Load Index (NASA-TLX). NASA-TLX offers a broader evaluation of cognitive workload using six dimensions (performance, mental effort, frustration, task demand, physical demand, and temporal demand). Using subjective ratings alone to measure cognitive load has some limitations, but they can be combined with performance or psychological measures to give researchers a clearer picture of workload demands.

2. Physiological Measures

Research has proven that there is a direct relationship between certain changes in physiological state and a change in cognitive workload (Chen et al. 2016). An advantage of this relationship is the ability to measure human data at a high rate with a high degree of accuracy. Some physiological behaviors monitored to measure CW include "heart rate and heart rate variability, brain activity from ECG and EEG, GSR or skin conductance, and eye activity such as blink rate and pupillary dilation" (Chen et al. 2016, 18). However, executing this method comes at a price. The equipment used to measure this data is very cumbersome. For example, Chen et al. (2016) explains that using an EEG headset not only interferes with the user executing the task, but it is also very costly and difficult to implement.

3. Behavioral Measures

Behavioral measures track human biological activity that is performed to accomplish a task. Some examples of behavioral observations include eye-gaze tracking, mouse pointing and clicking, gait patterns, and gestures (Chen et al. 2016, 21). Chen et al. point out that behavioral measures can reflect mental states, including cognitive load. An example is eye-tracking to measure learning and speech cues associated with high cognitive load (Chen et al. 2016).

Measuring and understanding CW is a large field of study. With increased understanding of CW, researchers and engineers can optimize systems to lower workload for human operators. A very popular method for mitigating workload for the Department of Defense is the automation of operator tasks.

D. HOW AUTOMATION CAN REDUCE PILOT COGNITIVE WORKLOAD

One of the critical duties for a MEDEVAC pilot is to facilitate the effective and efficient evacuation of injured warfighters. To help pilots achieve this objective, we seek to utilize computational methods to develop more efficient human-machine interaction. Automation can help the human counterpart lower the cognitive burden of dynamic missions by executing a task previously performed by the human operator (Parasuraman 1992). The level of automation can vary based on the needs of human operators. Automation assistance can range from a simple task, such as calculation, organizing, and storing information, or as complex as carrying out an entire action previously performed by a human, including aspects of flight. In each of these cases, automation serves to help the human operator at different levels of the given task.

By understanding cognitive workload and the factors that contribute to it, system designers can optimize systems for human performance (Knisely, Joyner, and Vaughn-Cooke 2021). Doing so requires solutions that address the human-machine system components together and find ways to enhance the total system performance. Humans must be present to make difficult decisions based on risk and multiple information inputs because algorithms and artificial intelligence cannot yet reliably make those decisions (Chen et al. 2016). Therefore, we must understand ways to manage workload to understand the variables that affect it and find ways to assist human operators and reduce the amount of information they must manage.

As technology develops, human's work becomes increasingly more cognitive than manual in nature. We must now manage our mental workload just as we manage physical workload (Parasuraman 1992). Parasuraman (1992) discusses some methods of managing cognitive workload such as avoiding tasks, prioritizing tasks, and getting computer/ machine assistance. He further discusses various approaches for automation. These include adaptive aiding of the human operator and shared task allocation from human to machine. Adaptive assistance can be described as those tasks where a computer and human operator trade tasks at appropriate times, in such a way as to maximize human performance (Parasuraman 2001).

Figure 2 shows the concept behind adaptive automation (assistance); the computer assumes tasks from the operator when cognitive workload is too high. When the operator's attention is available, tasks can be reallocated back to the human.

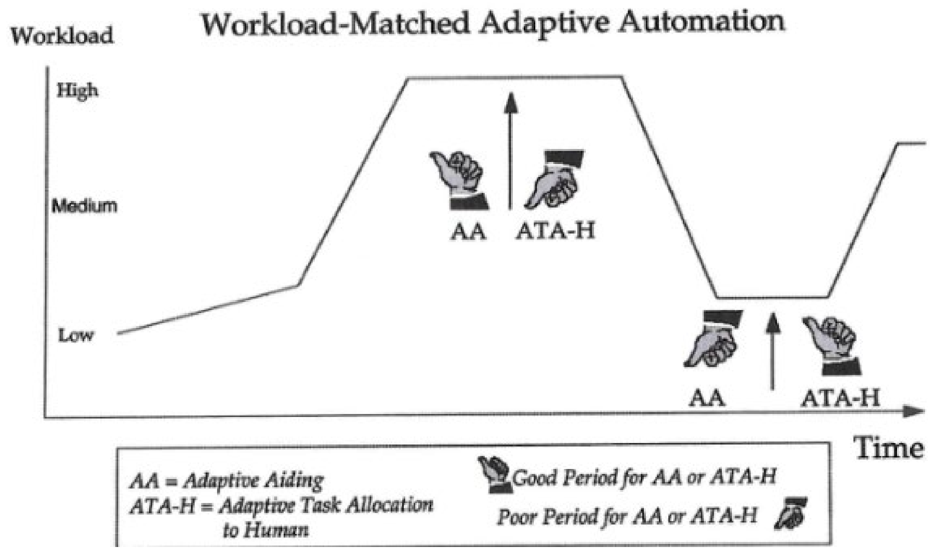


Figure 2. Adaptive Automation Task Trade-off. Source: Parasuraman (2001).

Automation has a role in the technology of modern-day aircraft systems. There is some debate on the optimal degree of automation for pilots. The amount of automation in a system exists on a spectrum, with advantages and disadvantages to be weighed depending on how much is applied. For example, "automation not only improves safety by reducing human error, but also increases" task performance reliability and precision, and reduces operator workload (Billings 1991; Hart and Sheridan 1984). Furthermore, operator fatigue accumulates at a reduced rate, and the "human operator has a greater capacity to perform more critical tasks" because of the reduced workload resulting from automation (Secarea 1990, 767).

Depending on how automation is implemented, it can sometimes have the opposite effect from what was intended, increasing CW for human operators. Research shows "that the increase in workload can degrade performance as the pilot reaches cognitive saturation" (De Visser et al. 2008). By studying these relationships, system designers can fine-tune the level of workload best suitable for future human-agent relationships. "The ultimate objective is to reduce system complexity and enhance operator performance by leveraging automation where it can be most beneficial and appropriate" (De Visser et al. 2008, 221).

Since automation has the potential to significantly reduce workload, it is beneficial to explore possible uses for its implementation. This must be done in a way that benefits the operator and does not cause more work or stress to them. Modeling and simulation methods allow researchers to analyze system tasks and how automation can provide the most benefit.

E. MODELING COGNITIVE WORKLOAD

There are many modeling and simulation tools available, each with various benefits and weaknesses. For the purpose of our capstone project, the most suitable tools are human-performance modeling tools. Wu, Rothrock, and Bolton (2019) explains that human performance modeling aims to examine human behavior and cognition to help develop a system's design to maximize user experience and engagement. This aligns precisely with our objective of analyzing cognitive workload to determine which tasks to automate, and ultimately to improve the pilot's performance.

Although we were able to narrow our list of modeling methods by focusing on human performance modeling, there were still several human performance modeling tools to evaluate. The tools we considered included human-in-the-loop, mathematical modeling, computer modeling and simulation, and discrete event simulation.

1. Human-in-the-Loop Modeling

Human-in-the-loop (HITL) modeling involves "building and testing multiple system designs and subjectively measuring the amount of workload experienced by each test subject" (Andrews et al. 2020b, 46). It is very informative because the operator is physically experiencing the workload and can detect changes in workload when the system design is changed. This information can be invaluable to researchers; however, it was not feasible for our study because it requires multiple prototypes which would have been expensive and time-consuming. Additionally, the operator data is subjective and may not generalize to the user population (Andrews et al. 2020).

2. Mathematical Modeling

Mathematical models quantify relationships between human behavior variables (Wu, Rothrock, and Bolton 2019). They are used to "predict, quantify, and analyze human performance, workload, brain waves, and other indices of human behavior" (Wu, Rothrock, and Bolton 2019, 470). Wu, Rothrock, and Bolton describe some of the benefits of using mathematical modeling, including its accuracy, ability to identify otherwise unknown variable relationships, and ability to easily integrate with other models. Additionally, they assert that there are complete mathematical models of the entire cognitive system in existence, which affords researchers the ability to extract portions for their needs. That said, mathematical models cannot stand alone, because they do not simulate behaviors. They are more beneficial in research focused on the relationships between variables. For our purposes, we want to simulate cognitive workload under various scenarios, so mathematical models were not sufficient to accomplish our goal.

3. Computer Modeling and Simulation

While computer modeling and simulation are not new concepts, developing "predictive models of human performance rather than simply descriptive models" has gained traction only in recent years (Laughery 1999, 816). Computer modeling and simulations allow researchers to measure human performance and to investigate the implications of manipulating various factors. For example, we can use computer algorithms to replicate cognitive workload (Laughery 1999). Likewise, Laughery (1999) asserts that simulations allow human factors to gain traction in popular design engineering disciplines that rely heavily on the use computer models, adding focus and credibility to the human factors discipline. Simulation, for our purposes, can be used to develop environmental conditions in which computer algorithms predict human cognitive workload.

Because all simulation is done in a virtual environment, it is less resource intensive than acquiring special equipment. Simulation also provides the flexibility to replicate various conditions that would be difficult to achieve in human-in-the-loop studies. Replicating these conditions allow us to simulate human behavior, which mathematical models fail to do. For our project, we used computer modeling, specifically discrete-event simulation software, to predict pilot workload.

4. Discrete Event Simulation and Multiple Resource Theory

Discrete-event simulation allows us to develop a virtual scenario in which one or more humans perform functions in a particular order, which helps us to model human behavior (Laughery 1999). Laughery describes this element of discrete-event simulation as task network modeling. He emphasizes that this has been used to model human performance in increasingly complex systems. Some benefits of task network modeling include the ability to map human tasks and system functions and the interoperability of these models with other complex models. Additionally, these models aid engineers in analyzing human-systems integration.

Multiple resource theory (MRT) is often used as the foundation of discrete-event simulations when studying cognitive workload (Laughery 1999). The main premise of MRT is that "humans have …several different resources which can be tapped simultaneously" (Laughery 1999, 819). Laughery explains that these resources may be used sequentially or in parallel. He also describes four channels that these resources can be broken into: visual, auditory, cognitive, and psychomotor (VACP). Additionally, MRT provides standard scales for each resource channel that can be used to measure workload (Laughery 1999).

This theory, and the use of discrete-event simulation, aligns with our goal of applying computer modeling to measure cognitive workload and analyze what should be automated. The next step was to find a tool that provided these capabilities.

F. IMPROVED PERFORMANCE RESEARCH INTEGRATION TOOL (IMPRINT)

IMPRINT is a computational human performance modeling tool that provides the ability to analyze multiple designs (Andrews et al. 2020a). It is a proven system used by ARL since the 1990s to model aspects of human behavior such as "task analysis, workload modeling, embedded personnel characteristics data, amongst others" (Salvi 2001, 2). It uses Multiple Resource Theory to develop discrete event simulations (Andrews et al. 2020b). IMPRINT was developed to analyze human performance as an element of the system acquisition process and has been heavily used by National Aeronautics and Space Administration (NASA) for similar purposes (Foyle and Hooey 2008). The capabilities of IMPRINT have been used to model a variety of elements, such as manning considerations for a production line (Powers and Gacy 2018) and performance degradation of different clothing and equipment factors (Salvi 2001). Recently, however, it has been heavily used to model different aspects of human-automation teaming for a variety of different systems to study the possibilities of autonomous or semi-autonomous systems (Pop 2018; Andrews et al. 2020a).

For the purposes of our research, IMPRINT has many relevant aspects. First, it provides the ability to model human performance tasks. This begins with a task network, which is a graphical depiction of the various task's humans conduct to achieve a given mission (Rusnock and Borghetti 2016). This task network is precisely what we developed from our pilot interviews. From this task network, a variety of tools are available to model specific elements of human behavior.

IMPRINT also uses the MRT VACP scale to model workload by simulating different configurations of variables and analyzing their effects (Andrews et al. 2020a). Andrews et al. (2020a) describe how VACP can be used to forecast the pilot workload associated with piloting an aircraft while simultaneously controlling UAVs. They identified tasks using a HITL evaluation, but this could also be accomplished by survey or other research method, as our research team. Each task was assigned a "VACP workload value, task time, and decision probability" based on the data derived from the evaluation (Andrews et al. 2020a, 174). In their study, Andrews et al. developed and compared an aircraft-only model with a manned-unmanned team incorporating a piloted aircraft and UAVs. In each model, they evaluated the overall mission performance and the cognitive workload of the pilot to determine how manned-unmanned teaming affected mission outcome. Andrews et al. concluded that mission performance increased with the human-automation teaming and that the cognitive workload of the pilot was manageable until the pilot received communication tasks. This increase in communication tasks caused a spike in cognitive workload (2020a). This research indicates that communication tasks require significant workload and provides room for future research on how to reduce that workload. We used this study as inspiration to investigate workload associated with communication tasks and potential impacts of automation on communication tasks.

IMPRINT was chosen as our modeling tool of choice because it is a proven tool in CW research. Rusnock and Borghetti (2016) discuss how many aspects of IMPRINT models have been validated by various methods throughout the years. they discuss how verification, validation, and accreditation (VV&A) was used to validate IMPRINT's predecessor, and how performance degradation factors and other elements have also undergone validation efforts. In addition to validating the tools, Rusnock and Borghetti (2016) describe how multiple studies have been conducted to validate various workload models that have been produced by IMPRINT, observation studies, experiments, and comparisons of models to subjective data collections, such as surveys and interviews. Based on these data, they conclude that IMPRINT tools such as the cognitive analytic workload profile (CAWP) accurately capture and model human behavior more beneficial than more subjective models. Furthermore, CAWP are less biased, more objective, and can provide additional data such as workload associated with various resource channels and workload over time (Rusnock and Borghetti 2016). Prior validation efforts as described above add a level of credibility to IMPRINT's tools that helped substantiate its use in this capstone project. Additionally, it emphasizes the benefits of possible follow-on efforts to verify the models produced by the capstone team.

While IMPRINT can be beneficial in modeling and analyzing pilot tasks and automation considerations, it does have some limitations. IMPRINT incorporates several tools to provide human performance modeling solutions, but it does not contain embedded model processes, such as cognitive or psychological processes. (Foyle and Hooey 2008). As Foyle and Hooey point out, the modeler is required to "specify and implement these constructs" (2008, 71). It does not contain templates for every scenario, so the modeler must be able to manipulate IMPRINT to account for specific variables. Adequate training is required to fully utilize IMPRINT's capabilities and properly manipulate the settings to operate as required.

IMPRINT is also extremely reliant on the modeler to develop accurate models because the accuracy of the model is dependent on the model inputs (Rusnock and Borghetti 2016). IMPRINT is not a measurement tool, but a modeling tool, so those measurements, tasks, or other variables must be manually input into the software to be modeled and analyzed. There is always human error associated with manual inputs. Additionally, while IMPRINT can capture many aspects of task workload, including task difficulty and quantity, "it does not inherently account for time-on-task fatigue, experience, and learning" (Rusnock and Borghetti 2016). These elements may have a large impact on cognitive workload but are not directly accounted for in the model. Some of these elements can be indirectly accounted for through analysis of different factors. This could include inferring time availability through analysis of task success or failure percentages and inferring the impact of environmental factors through analysis of task accuracy and timing (Rusnock and Borghetti 2016).

These limitations do not outweigh the benefits and capabilities of the IMPRINT software. With proper training on IMPRINT and in-depth analysis of the outputs, this research team overcame the limitations and properly modeled and analyzed tasks to meet our objective.

To demonstrate how IMPRINT directly applies to our capstone project, we reviewed an analysis of the optimally crewed vehicle (OCV) that utilized IMPRINT modeling. This analysis, like the Andrews et al. study, informed the use of task networking for our model. It also provided the idea to use elements of established models, create sub-models, and reallocate tasks to investigate workload reduction techniques. The research, undertaken by Militello et al. (2019a), explored the concept of human-machine teaming with various aircraft, which was inspired by the research on the FVL program. The research followed an FVL case study that aimed to identify the optimal crewing configuration for the Future Attack Reconnaissance Aircraft (FARA) (Militello et al. 2019a). The research took place in three phases. In the first phase, Militello et al. (2019a) developed an initial optimal crewing strategy. In the second phase, they conducted task analysis through interviews and functional analysis through cognitive work analysis (CWA). They also developed an IMPRINT model and a trade space framework to analyze workload. They used five interview techniques to conduct task analysis, which included the critical decision method (CDM), task diagram technique, a knowledge audit, technology-focused interviews, and envisioner interviews. Critical decision method focuses on interviewees recollecting challenging issues rather than answering specific questions and identifying cognitive analyses from those recollections to gain key information (Militello et al. 2019a).Militello further pointed out that the task diagram technique focuses on asking the interviewee to break down specific tasks into steps and identify challenging elements . Knowledge audits are like CDM, they explained, in that they elicit recollections from the interviewees, but they use probes from expert literature to gain more information. Technology-focused interviews focus on alternative technologies and how these technologies could impact interviewees based on their experiences . Militello's final point is that envisioner interviews focus on how the SME interviewees perceive the future in the context of the envisioned technologies, in this case the FVL . The researchers compiled the results from these interviews to identify cognitive challenges and used to inform CWA.

Rather than start from nothing, Militello et al. (2019a) modified a similar, previously used, Apache IMPRINT model to analyze FARA pilot workload. They added specific tasks, based on the outcome of task analysis, and used various distributions of task and function allocations for the models. A task network was developed from these tasks, using VACP scales to analyze cognitive workload. The models incorporated various technologies, such as automated tracking and takeoff, and various scenario variables, such as number of crew members, environmental factors, and type of flight (Militello et al. 2019a). An attention model was incorporated throughout the model to determine where the pilot and copilot focus their attention and how long before they transition their attention (Militello et al. 2019a). These sub-models ran for the entirety of the input scenario. Once the main model was developed, Militello et al. incorporated and compared several configurations with various degrees of human-automation involvement. They also evaluated alternative task allocations by reassigning tasks between the human and machine elements to analyze the impacts on workload. This research informed how we approached our research, highlighting how specific conditions may warrant different task automation techniques. Our research can inform a menu of task automation options, which may be tailored to different mission or environmental conditions.

Militello et al. provided important insight into how to approach IMPRINT modeling. Our literature review showed us how starting with a task analysis is the most useful path. We modeled our task analysis process after a study from the Army Research Institute (ARI). In 1988, the ARI published a series of task analyses for UH-60 and CH-47 helicopters. The purpose of these studies was to establish a baseline for pilot cognitive workload during basic flight and in different conditions (Bierbaum, Szabo, and Aldrich 1988). While this work is aged, the authors used a simple and practical methodology for their task analysis that was easily adapted to this team's work. Bierbaum, Szabo, and Aldrich first developed a mission scenario and divided the mission into phases. In the case of our work, we focused on the phase of steady flight, after take-off and prior to entering approach. They then divided their phases into segments. We organized our tasks by type: Aviate, Navigate, and Communicate tasks. From there, the authors identified and analyzed the individual tasks within each function. We identified our tasks using the 2021 UH-60 Aircrew Training Manual from the Aviation Center of Excellence at Fort Rucker, AL and by interviewing UH-60 pilots. With the tasks identified, Bierbaum, Szabo, and Aldrich interviewed pilots to assign workload values to each individual task. We did this as well but using the VACP values. We also developed a pilot interview format which introduces the subject to our purpose and research question and explained how VACP data would inform our model. We utilized the task diagram interview technique to elicit subtasks and challenge areas. The pilot then walked us through each task and provided their subjective values based on what they believe a pilot would experience for that task during flight. Once we interviewed six pilots, we were able to combine the workload values and insert them into the tasks we built in IMPRINT.

G. PILOT COMMUNICATION

IMPRINT can simulate various pilot tasks that affect cognitive workload, including the ability of the pilots to communicate. In a 2021 presentation at the Naval Postgraduate School, HSA-DM project director Mr. Matt Shivers discussed his interest in the communication elements of a flight. We decided to focus on these tasks specifically because of this interest from our stakeholders. It is also supported in the research literature. We have already seen in the 2020 Andrews et al. article that communication tasks cause a spike in pilot workload. We are focused on two types of communication tasks in our research: internal and external. Internal communication encompasses the communication between the pilot and copilot. External communication occurs between either pilot and an entity outside of the aircraft, which could include air traffic control, the pilot's unit, or the unit requesting the MEDEVAC. Pilots and copilots have almost the same functional abilities within the cockpit and generally decide who will do what prior to the flight. MacIsaac (1998) explains that "crews must agree on what each will each bring to the cockpit workload, and then cooperate verbally" (5).

Communication between pilots is crucial to the safe operation of the aircraft. There have been several crashes that were attributed to a lack of pilot communication (MacIsaac 1998). MacIsaac discusses a 1983 crash in which poor visibility and inadequate internal communication led to the pilot unintentionally descending into the sea. In this case, the communication breakdown was due to the pilot and copilot not communicating the need to cover different sectors of view outside the aircraft's environment to improve navigation. MacIsaac also discusses a Portland crash in 1978 that was caused by the pilots not monitoring the fuel state, or not communicating it, and running out of fuel. This case resulted in the FAA Air Carrier Operations requiring "interpersonal communications training for air carrier flight crews" (MacIsaac 1998, 5–6). As a result, "crew resource management programs have since made their way into helicopter crew training in both the military and civilian sectors" (6).

Crew communication is vital. In fact, it is so important that the UH-60 series Aircraft Training Manual (ATM) has a tab hyperlinked to "Aircrew Coordination Training" at the top of every page for quick reference (ATM 2022). A key component of this aircrew coordination is communication. The ATM provides detailed guidance on internal communication:

- Communicate Positively

- Be explicit
- Announce Actions
- Acknowledge Actions
- Direct Assistance
- Offer Assistance
- Coordinate action sequence and timing
- Provide aircraft control and obstacle advisories (ATM 2022, 7 – 2).

These guidelines stress the importance of maintaining situational awareness through communication. This means that the pilot and copilot are constantly communicating throughout the flight, providing announcement and acknowledgement for each subtask (ATM 2022).

Internal communication tasks occur in addition to the external communication requirements, which are primarily conducted by the copilot (ATM 2022). The 2022 ATM specifies that the primary focus of the pilot is flying the aircraft, scanning instrument displays, and monitoring the radios. Pilots are required to maintain communications with an air traffic control facilities and may have additional requirements with their unit (ATM 2022). They may transmit as required, but the copilot generally handles most of the external communications. The copilot manages the rest of the flight operations. These tasks include tuning the radios, navigating, communicating with external entities, completing fuel and power checks, and adjusting internal systems as required (ATM 2022). In a real-world MEDEVAC mission, it is easy to see the complexity of internal and external communication requirements.

In a MEDEVAC scenario, pilots would ideally be in communication with the patient's unit, air traffic control station and the pilot's operations channel. According to UH-60 Flight Instructor CW3 Alexander Wilson, communication requirements increase the closer the aircraft gets to the patient (Wilson 2022). Additionally, CW3 Wilson explains that in current UH-60 models, when monitoring multiple frequencies simultaneously, radio traffic may overlap. It is up to the pilot to listen for their call-sign for key information. Managing all these frequencies can become chaotic in dynamic situations where pilots are communicating with numerous entities, such as when approaching a patient's location.

External communications also lead to more internal communication requirements because the copilot must announce any information that the pilot is not monitoring and vice versa, but also includes copying down key information (ATM 2022). Likewise, communication is not strictly voice communications, because some external communication entities may be outside of radio frequency range. UH-60s are equipped with blue force tracker (BFT) capabilities using the Global Positioning System (GPS) to provide situational awareness of the UH-60's exact location beyond line-of-sight messaging (ATM 2022). CW3 Wilson describes how sending messages using the BFT can be cognitively challenging, because the keyboard does not follow the traditional QWERTY format but is in alphabetical order (Wilson 2022). This need to focus on typing a time-sensitive message adds a layer of complexity to an already complex communication situation. A crew may be required to monitor five external frequencies, a BFT, and the ICS for internal communications, all while executing aviation and navigation tasks (Wilson 2022). Because of the complexity of communication tasks and the associated potential cognitive workload, we focused most of our efforts on identifying opportunities for automation within these tasks.

H. SUMMARY

This discussion on pilot communications brings us back to the question at hand: To what extent is workload reduced if specific pilot communication tasks are automated? This literature review provides the basis to answer this question by delving into key topic areas that support this research question. We began by discussing the premise of our capstone project, which builds on the research and efforts of a prior capstone team. We then discussed the goal and purpose of the FVL and HSA-DM to provide background information on the system and key stakeholders. We discussed the complexities of cognitive workload, potential effects of automation on cognitive workload, various ways to measure cognitive workload, and various methods used to model cognitive workload. This extensive research served to narrow our focus on specific aspects of workload to measure and model to answer our research question. This research led us to the IMPRINT tool, which is a proven human performance modeling tool and is best suited to model workload for the purposes of our capstone. This is due to the variety of tools available, the lack of extensive resources and costs required, and its overall credibility. Using IMPRINT to model the effects of automation on pilot communication tasks will help our stakeholders determine what tasks should be automated on the next generation FVL and potentially inform follow-on projects as a result. In the next section we outline the methods and approach that we utilized to analyze these tasks, develop an IMPRINT model, and assess potential automation opportunities.

III. METHODS

A. OVERVIEW

The primary purpose of this capstone project is to develop a human performance model to assess whether the automation of certain communication tasks will mitigate pilot cognitive workload in the FVL. In this chapter, we will discuss the participants of the study, equipment used, and the procedures we followed to answer our research question. Our general approach was to use input from active rotary-wing pilots and current literature on cognitive workload to develop a task analysis. We built the task analysis into IMPRINT to generate models with cognitive workload values assigned to each task. The models were modified to simulate automation of high-workload tasks, and then analyzed for model validity, impact on workload, and feasibility of recommended solutions. We then generate recommendations of tasks to automate for the HSA-DM team.

B. PARTICIPANTS

Rotary-wing pilots provided the data and expert knowledge required to build our IMPRINT models. We conducted pilot interviews, cognitive walkthrough of all tasks, and received support from an IMPRINT subject matter expert (SME) to build our models. The pilot interviews and cognitive walkthrough helped the team develop an understanding of flying rotary-wing helicopters and how to accurately depict tasks performed during a routine flight within our model. We were also able to validate our assumptions made about tasks performed during a flight with accurate VACP values assigned to each task.

Prior to conducting interviews and walkthroughs, the researchers submitted a determination request to the NPS Institutional Review Board (IRB). Because we interviewed pilots, we were required to request IRB approval before interviews were conducted. The IRB determined that the study did not require an IRB review and approval because our results are not intended to be generalizable.

To start our research, we needed to gain a better understanding of how pilots operate their aircraft and the associated cognitive workload. We recruited and collected data from six certified U.S. Army rotary-wing aircraft pilots. The pilots' experience in their respective aircraft ranged from 500 to over 2,100 flight hours. Table 2 provides the breakdown of each pilot's experience. The details of how we leveraged the pilot's experiences are presented in Section C, Procedures.

Table 2. Pilot Flight Hours and Experience

Pilot Info		
Pilot	Total Career Flight Hours	Total years of flight experience
P1	500	8
P2	600	8
P3	1,300	8
P4	3000	12
P5	2500	8
P6	2100	15
Total Flight Hours/Years Experience:	10000	59

C. EQUIPMENT

IMPRINT, described in detail in Chapter II, is the primary tool that we used for our analysis. To understand IMPRINT and use it to its full potential, we engaged in IMPRINT training with a subject matter expert, Bob Sargent of Huntington Ingalls Industry. This training provided us with a baseline understanding of IMPRINT, the foundational theory behind IMPRINT's workload analysis – Multiple Resource Theory, and a hands-on exercise to develop a workload model. Sargent also continued to provide advice throughout the development and testing of our model. The IMPRINT tools used in our study include task analysis, human performance modeling, VACP scaling, and various reports to analyze the data. Further details about the specific IMPRINT procedures are explained in Section.

D. PROCEDURES

Developing our IMPRINT cognitive workload model required several steps. Bob Sargent (2021) outlined a 10-step process for building an IMPRINT analysis during his initial IMPRINT training session at the Naval Postgraduate School:

1. Defining the objective

2. Designing the study
3. Collecting input data
4. Defining the mission
5. Developing the task data
6. Debugging the model
7. Running the study
8. Collecting output data
9. Analyzing the data
10. Presenting the results

Our analysis follows this approach but instead is broken down into three phases. In Phase I of this project, we began with a broad analysis of literature to inform the direction of our research. This phase comprised steps one through four of Sargent's approach. Phase II is task analysis, which includes steps four and five. Phase III includes the development, validation, and results analysis of the IMPRINT models, covering steps six through nine. Chapter IV of this report covers step 10, presenting the results. The following sections present an in-depth discussion into the methodology for each of these phases.

1. Task Analysis

The task analysis approach we followed was the task analysis/workload (TAWL) methodology outlined in a research report by Bierbaum and Hamilton (1991). Bierbaum and Hamilton conducted their research on the MH-47E aircraft to develop a cognitive workload model, similar to our project. While the research and report are relatively old, the methodology is still a valid technique to conduct task analysis. The methodology began by collecting pilot estimates of cognitive workload associated with a specific mission, in our case, the MEDEVAC mission. Next, we broke the mission down into phases, segments, functions, and tasks (Bierbaum and Hamilton 1991, x). We initially began by using the 2021 *UH-60 Series Aircrew Training Manual* to gather this information and select tasks to model. Based on conversations with the UH-60 pilots, we realized that these tasks were too broad to allow us to provide recommendations for automation. At this point, we decided to conduct the cognitive walkthrough interviews to identify lower-level tasks that would provide us a detailed picture of the steps required to fly a UH-60 and the flexibility to experiment with automation.

We followed an approach similar to Militello et al. (2019) previously described in Chapter II to elicit information from the pilots. In particular, we used both the task diagram and knowledge audit approach, or cognitive walkthrough, to collect the data. We conducted interviews with pilots for two reasons: first, to gain an understanding of the individual tasks they performed during flight, and second, to record their subjective CW values using the VACP scale. Our knowledge audit interviews provided extensive, first-person descriptions of how pilots operate their aircraft, the tasks and subtasks involved, and the VACP values associated with each task. The conversations with these pilots were invaluable for our research, allowing us to gain understanding of flight tasks. These conversations enabled us to develop the most accurate model possible. The development of our model is explored in depth in Section C.2.

Each interview began with collection of general background data on the pilot's training, years of flying and flight hours depicted in Table 2. These data were compiled to ensure each pilot had a sufficient amount of flight experience and diverse knowledge. Next, we conducted the knowledge audit or cognitive walkthrough portion of the interview by asking the pilots to describe each step of their flight as if they were in the cockpit. Based on the cognitive walkthroughs, we generated a task analysis of all tasks conducted during routine flight. We then had the pilots describe the VACP workload values associated with each task, along with the time required to complete the task, standard deviation of each task, and frequency of each task per flight. They also identified the primary holder of each task based on current task ownership. The three primary task holders among whom tasks are divided are the pilot, copilot, and automated system. For the purposes of this project, the pilot is the one on the flight controls, the copilot is generally off-controls. To identify which VACP values to assign to the tasks in our IMPRINT model, we consolidated all information from the pilots and evaluated each task individually. When assigning workload values, our primary approach was to use the consensus values or mode of the pilots' responses. If there were any discrepancies between the pilot answers, we would take the mean value. During the IMPRINT class, Bob Sargent stressed the importance of making sure to avoid double accounting for workload. For example, in Task 13 “scan external environment,” there is significant visual workload involved, and there is some cognitive workload associated with that task as well. Some of the pilots were double accounting for the visual workload in the cognitive workload values, by providing larger values for cognitive workload than would be realistic. In these scenarios, we discussed if each of the values was realistic, and then went back to the pilots to determine if our understanding was accurate. This information allowed us to input accurate data into the IMPRINT model to generate a realistic depiction of pilot and copilot workload in flight.

Table 3. Task Analysis

			Identify Obstacles		70%	only when needed. ~ 1 hour	~30 second	+/-7 seconds	0	5	4.6	0	6	
	Copilot			Conduct Evasive Mvrs		when needed								
		Instrument Scans												
			Scan Primary Display		50%	~5 minutes	2-3 seconds	+/- 1 second	1	1.2	0	0	1	
			Scan Secondary Display		50%	~5 minutes	2-3 seconds	+/- 1 second	1	1.2	3.6	0	1	
		Airspace Surveillance												
			Scan External Environment		40%	~5 sec	2-3 seconds	+/- 1 second	**0**	4.6	0	**0**	5	
			Identify Obstacles		30%	~ 15 minutes	~ 15 seconds	+/- 3 seconds	**0**	4.6	0	**0**	6	
		Manage Flight Ops							0	0	0	0	0	
			Fuel Management Procedures		100%	Within 10 after leveling off or within 10 minutes of entering mission			0	5.3	6.5	0	3	
				Announce when doing fuel	100%		3s		**0**	**0**	**0**	**2**	**0**	
				Take Initial Fuel Reading	100%		5s	2s	**0**	**1**	**0**	**0**	**3**	
				Take Second reading, calculate	100%	15 minutes after initial	3 min	1min	**0**	**7**	**5.5**	**0**	**3**	
			Record the total fuel quantity and the time of reading						0	0	6	0	0	
			Complete the fuel consumption check						0	4.6	0	0	3	
			Balance/manage fuel tank levels to maintain aircraft within CG limits						0	4.6	0	0	0	
Naviagate														
	Pilot/Copilot	Announce shift internal							0	0	0	0	0	
		Operate Digital Map	Operate bezel keys on the MFD		50%	~5 minutes	~1 sec	n/a	0	0	2.2	0	0	
			Operate the collective slew controller		50%	~ 10 minutes	~15 sec	+/- 3 sec	0	0	5.5	0	0	
			Operate the multifunction slew controller (MFSC) or the collective cursor slew controller to gain desired information and to manipulate desired mission data on the		50%	~ 10 minutes	~15 sec	+/- 3 sec	0	0	5.5	0	0	
Communicate														
	Pilot													
			Transmit Information		50%	~ 5 min	2-3 sec	+/- 1 sec	**0**	**1.2**	**2.2**	**4**	**0**	
			Receive Information		50%	~ 5 min	2-3 sec	+/- 1 sec	**6**	**1.2**	**0**	**0**	**0**	
		External Communications												
			Monior Radio Channels		50%	~ 5 min	2-3 sec	+/- 1 sec	**0**	**0**	**0**	**0**	**1**	
			Select Radio Channel for transmition (Radio)		50%	~ 5 min	2-3 sec	+/- 1 sec	0	0	0	0	1	
			Transmit Information (Radio)		50%	~ 5 min	2-3 sec	+/- 1 sec	**0**	**1.2**	**2.2**	**4**	0	
			Input Radio Freq		50%	~ 5 min	2-3 sec	+/- 1 sec	0	0	5.5	0	3	
			Adjust Volume	Identify which channel is	50%	~ 5 min	2-3 sec	+/- 1 sec	0	0	5.5	0	0	
	Co-Pilot													
		Internal Communications												
			Transmit Information		50%	~ 5 min	2-3 sec	+/- 1 sec	**0**	**1.2**	**2.2**	**4**	**0**	
			Receive Information		50%	~ 5 min	2-3 sec	+/- 1 sec	**6**	**1.2**	**0**	**0**	**0**	
		External Communications												
			Monitor Radio Channels		50%	~ 5 min	2-3 sec	+/- 1 sec	**0**	**0**	**0**	**0**	**1**	
			Select Radio Channel for transmition		50%	~ 5 min	2-3 sec	+/- 1 sec	0	0	0	0	1	
			Transmit Information (Radio)		50%	~ 5 min	2-3 sec	+/- 1 sec	**0**	**1.2**	**2.2**	**4**	0	
			Input Radio Freq		50%	~ 5 min	2-3 sec	+/- 1 sec	0	0	5.5	0	3	
				Identify which channel is										
			Monior JVMF		100%	Only when a message arrives	~20 seconds	+/- 3 sec	0	4.6	2.2	0	3	
			Send Message		100%	~ 1 hour	~2 minutes	+/- 30 sec	0	4.6	5.5	0	3	
			Receive Message		100%	Only when a message arrives	~ 20 seconds	+/- 3 sec	0	4.6	2.2	0	3	
			Adjust Volume		No volume that I can recall									
			Record Information		100%	~ 1 hour	~ 1 minute	+/- 10 sec	0	4.6	5.5	0	3	

At this point, our methodology veers from that of the Bierbaum and Hamilton (1991) report. This is because Bierbaum and Hamilton used the TAWL Operator Simulation System (TOSS) software to develop workload predictions. We instead used IMPRINT to develop workload models for the reasons discussed in our literature review. Our next step was to use the task analysis to develop an IMPRINT model.

2. IMPRINT Model Development and Validation

a. Method

Our IMPRINT model was built based on the task analysis performed in Phase II. We began by inputting the tasks and values derived from our task analysis into a sequential model. The next step was to "debug" the model by ensuring that all elements of the model were linked correctly and by verifying task components for accuracy with MEDEVAC pilots. Once the model was "bug-free" and the contents verified for accuracy, we could run the model.

To meet our research objectives, we ran several models in which we variously allocated the tasks that were owned by the pilot, copilot, and automated system. This method allowed us to collect the output data on the workload for the pilot and copilot when certain tasks were automated. We then analyzed the results of these models and developed a list of communication tasks that exceeded a cognitive workload value of 60. The value of 60 is the threshold for cognitive overload gleaned from IMPRINT and indicates reduced performance beyond this level (Sargent 2021). To validate our model, we submitted it and the results to Bob Sargent and multiple MEDEVAC pilots to provide feedback on how well the model aligned with reality.

Figure 3 depicts our overall model. Our model organizes all pilot tasks into three groupings: aviate, navigate, and communicate. These are the high-level task categories that pilots must conduct to operate an aircraft. While our focus is on communication, to develop a realistic, robust model, we wanted to highlight the other two high-level task categories as well. All tasks are color coded based on who performs each task. Blue tasks represent actions performed by the pilot and green tasks represent actions performed by the copilot.

Black tasks show the tasks assigned to an "automation" operator. The baseline model does not incorporate automated tasks, but black tasks are incorporated in the modified models, as depicted in Figure 3. Purple tasks are model tasks, which provide structure and flow to the model but are not executed by an operator and have no CW values. The following sections explain how we organized tasks to develop the model. All model decisions, such as path logic, VACP values, and sequencing, were made based on the pilot interviews and validated by IMPRINT SME, Bob Sargent, and the six pilots upon completion of the model.

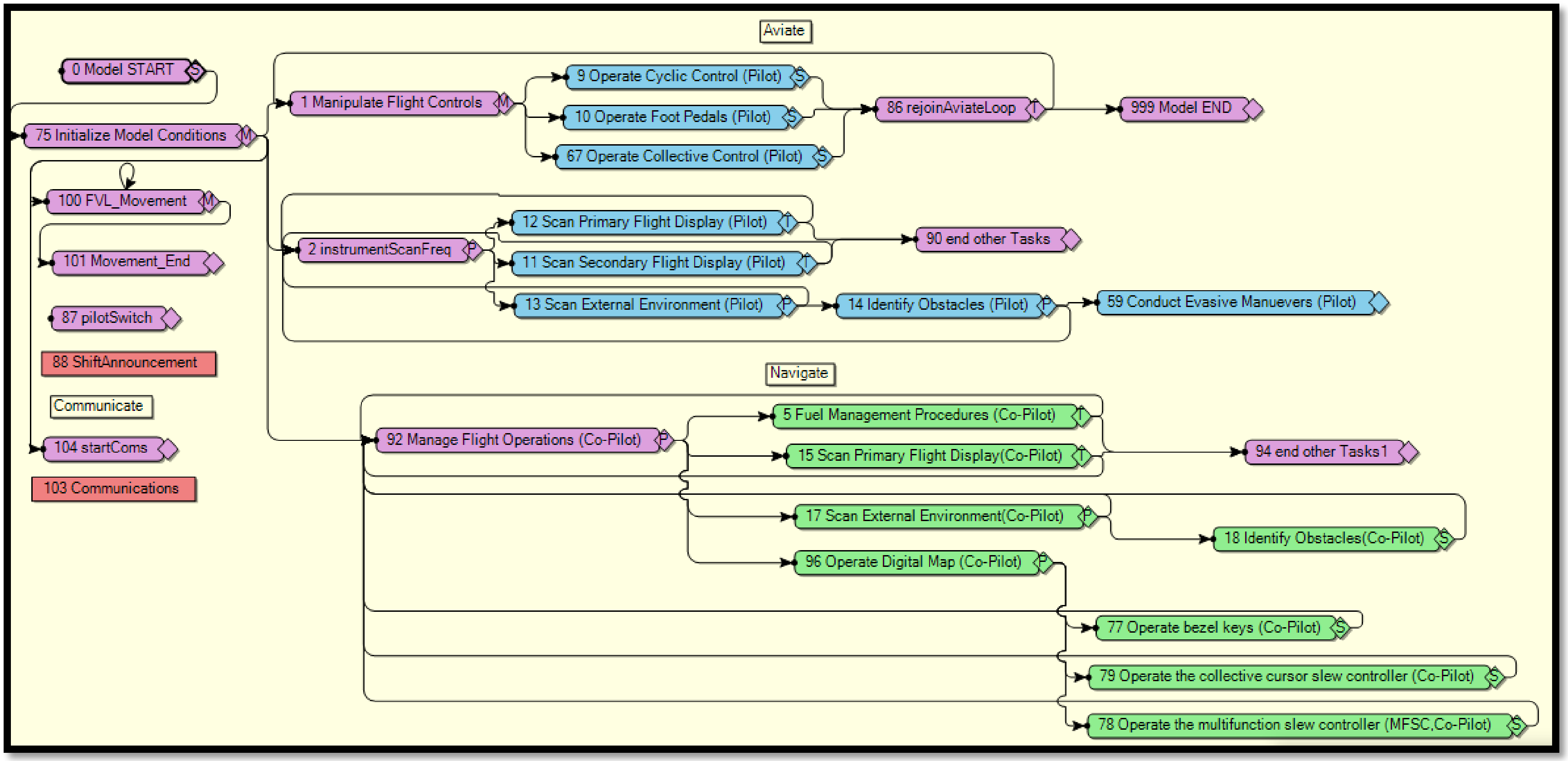


Figure 3. Complete IMPRINT Model View

b. Aviate

Figure 4 shows the breakdown of aviate tasks according to our pilot interviews. In aviate, the pilot and copilot are scanning their pre-coordinated sectors in space. While scanning, the pilot is manipulating the three flight controls (cyclic, collective, foot pedals) to maintain the aircraft in the flight. Occasionally, each pilot may quickly scan their instrument panel to verify their position in space (speed, torque, altitude, pitch). During flight, the pilot has the primary job of flying the aircraft. The copilot conducts all cockpit administration tasks such as fuel and power checks and monitoring communications (comms). The pilot monitors comms also, but it is primarily the job of the copilot to respond and manage the helicopter's comms. The methods of modeling communications is further explained in the communicate phase of the model.

To build this phase into IMPRINT, we used groupings of tasks to model the flight. We began with creating individual tasks that were derived from our task analysis. For each task, we assigned primary operators (pilot, copilot, or automation), as well as values for task frequency, time to complete task, standard deviation of that time, and VACP values. All task duration, frequency, and value assignments can be found in Appendix B of this report. The MRT workload demand values were averaged from discrete quantitative data received from licensed Blackhawk helicopter pilots.

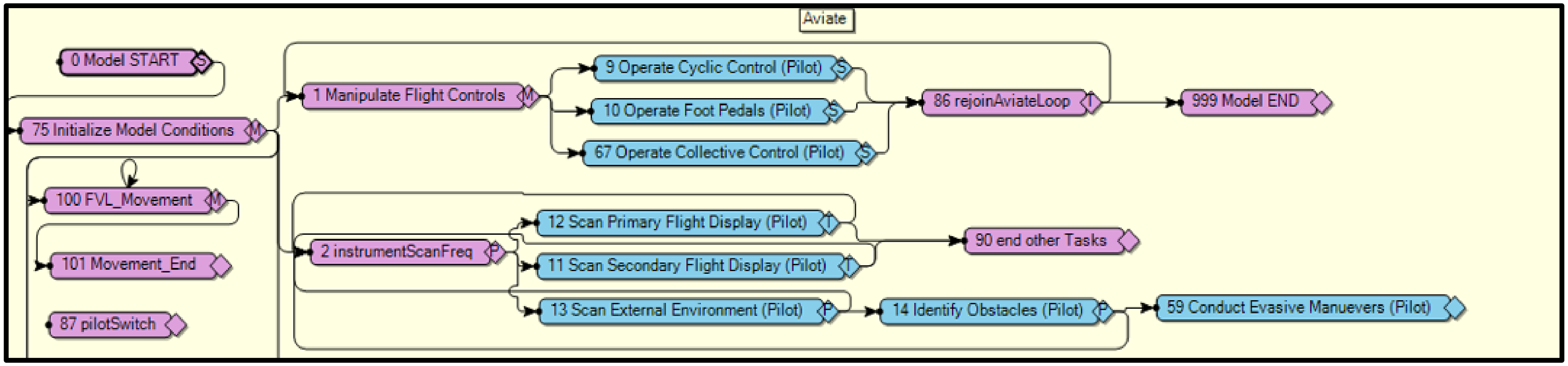


Figure 4. Aviate Section of IMPRINT Model

The next step was to sequence each task with path logic that accurately models those tasks in real life. Our first challenge in modeling was understanding how to model tasks that happen at random or irregular intervals. In our pilot interviews, one interviewee explained that much of what pilots perform is “METT-C dependent” – an Army jargon way of saying “it depends.” To account for the “it depends” in our model, we assigned variability to routine tasks. We modeled this variability and randomness in many places using probabilistic path logic. The logic follows a random path each time it is run, based on a probabilistic percentage that we assigned to the task (Sargent 2021). The probabilistic path allows us to simulate tasks happening sometimes individually or any combination of tasks executed simultaneously. The probabilistic path is displayed in Task 1: Manipulate flight controls in Figure 4. In Task 1, the pilot performs an action on one, two, or all three flight controls with varying combinations and probabilities. Any combination of the three flight controls could be manipulated at any given time.

Additionally, there are two other types of path logic used in our model: multiple and tactical. A multiple path can be used to execute multiple model tasks simultaneously. An example is Task 75: Initiate Model Conditions depicts a multiple path. This task allows the model to start simulating the aviate, navigate, communicate phases simultaneously; effectively directing the performance of the overall model. A tactical path allows us to demonstrate “either-or” scenarios in which it evaluates which task takes precedence and will flow through the highest value task or the first created task if all are true (or false). Task 86: rejoinAviateLoop depicts a tactical path that either continues the “manipulate flight controls” loop or ends the model depending on whether the “distance to zero >0” condition is true or false. In our model, we use tactical paths to ensure the model stops running when the distance variable reaches zero. In other words, when the mission is complete, all tasks will stop. This also depicts how we used task loops for task sequencing. For tasks that happen routinely over time, we assigned those tasks timing and frequency derived from pilot interviews. We sometimes looped several similar tasks so the sequence would occur multiple times throughout the flight, as seen in the “manipulate flight controls” and “InstrumentScanFrequency” task loops. We also included “ending logic” to end the tasks when the aircraft arrives at the destination.

Once we completed the aviate tasks and sequencing, we also created a goal, which is a scenario that can be triggered in the model as needed (Sargent 2021). Goals model human behavior based on priorities and conditions built into the goal. They are represented in the model by red blocks, as shown in Figure 3. The goal for aviate is the "shift announcement," which allows us to demonstrate what happens when the pilot needs to shift focus internally to the cockpit. The goal is triggered randomly throughout the flight to model the variable frequency with which it may occur. When triggered, the shift announcement goal "interrupts" the rest of the flight tasks, so that the only tasks conducted are those within the goal, to prevent unrealistic and excessive workload values. When the "shift announcement" goal is triggered, the model simulates the pilot transitioning to operate the multifunctional display. The copilot takes over flight controls and scans the entire external environment. We wanted to ensure we modeled the scenario where the two pilots effectively shift roles periodically. To ensure that we did not overlook the communication tasks that were happening at the same time, we also created a higher priority "communication" goal. The communication goal runs throughout the flight, including when the "shift announcement" goal is triggered, since it is a higher priority goal.

c. Navigate

In Aviate, we explained how the helicopter copilot is responsible for cockpit administrative tasks while the pilot focuses on flying the aircraft. In the navigate phase, the pilot and copilot continue scanning their sectors and the copilot performs navigation tasks. The navigate phase also involves the copilot operating the digital map throughout the flight. In our model, operating the map includes three interactions described in Figure 5: operate bezel keys, operate collective curser slew controller, and operate multifunction slew controller.

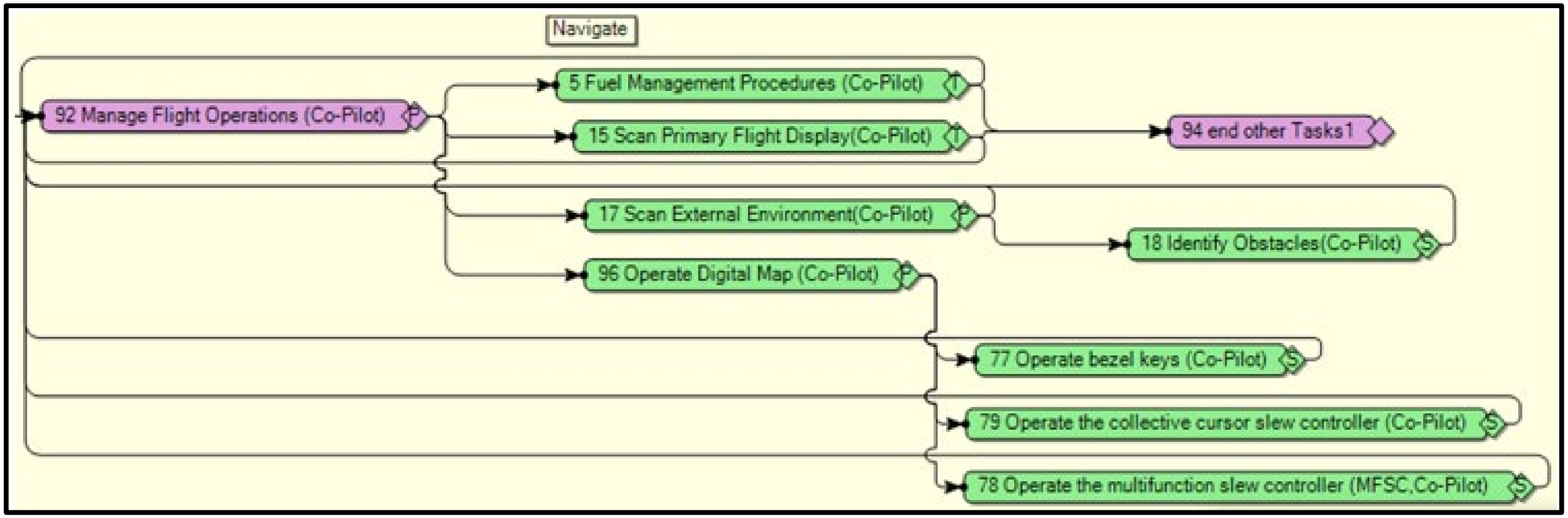


Figure 5. Navigate Section of the IMPRINT Model

We designed the primary task in navigation, “Manage Flight Operations” as a probabilistic node. Using a probabilistic node allows us to let the model determine which task is executed next based on the probability value it was assigned. Operate digital map has three subfunctions with equal distribution across the three subtasks to operate the digital map. We used an equal distribution of 33% across all three subtasks, because any task is as likely to be used by the pilot as another based on pilot preference. Once the “operate digital map” task is executed, one of the three subtasks is triggered. After the subtask has executed, it will loop back to start another loop of Manage Flight Operations. This looping continues throughout the model to simulate how the copilot is constantly juggling these tasks during flight. When the pilot chooses to operate the digital map, the model executes the “pilot shift internal” goal described in Aviate.

d. Communicate

The communication phase was the most difficult to model because we needed to simulate both internal communication between the pilot and copilot as well as external communications between the pilots and outside entities. External communications are usually with a sister aircraft, ground unit, control tower, or headquarters. Additionally, the model captures how each pilot monitored four external communication nets as well as the blue force tracker capability built into the aircraft’s Joint Variable Messaging Format (JVMF). Communications tasks are the focus of our research. We therefore created a “goal” for the communications tasks to ensure that these tasks continued running throughout the model, even when the “pilot internal focus” goal triggered. We also created time-delays to ensure that tasks were not happening at the same time unless that combination of tasks would happen in real flight. For example, the copilot could not be transmitting and receiving communications at the same time.

Our approach to modeling communications is illustrated in Figure 6 and comprises three branches: pilot external communications, copilot external communications, and helicopter internal communications. For pilot external communications, we assumed that the pilot is only listening to the radios and not responding during this phase, since responding to external comms is the copilot’s responsibility. This assumption is valid for the phase of flight we are modeling according to our pilot interviews. Task 103_3 PilotExternalReceiveComms starts a chain of tasks that model the pilot listening to external transmissions in their headset, while Task 103_22 Receive is associated with some auditory cognitive workload only. After a short delay, the pilot may adjust volume (103_28) if they want to listen more closely, or they may look at the display (103_29) to see which net is transmitting. Sometimes they do nothing at all and continue monitoring and flying.

The challenge to modeling copilot external comms was making the model work such that the copilot can monitor the internal net plus four external radios simultaneously but only transmits back on one net at a time. 103_15 Comms starts the chain of tasks that accomplishes this idea for us. Task 103_10 CoPilotExternalTransmit is a probabilistic node that chooses one task at a time when triggered. After a short delay, 103_10 CoPilotExternalTransmit gives the copilot the option of manually inputting a channel (103_24 input channel) and transmitting a message (5% probability), select a preprogrammed channel (103_25 select channel) and transmitting a message (80% probability), or sending a JVMF message (15% probability). These probabilistic values were derived from pilot interviews. Task 103_18 Co-PilotExternalReceiveComms includes tasks for the copilot to monitor the various nets and sometimes recording a note on their kneeboard.

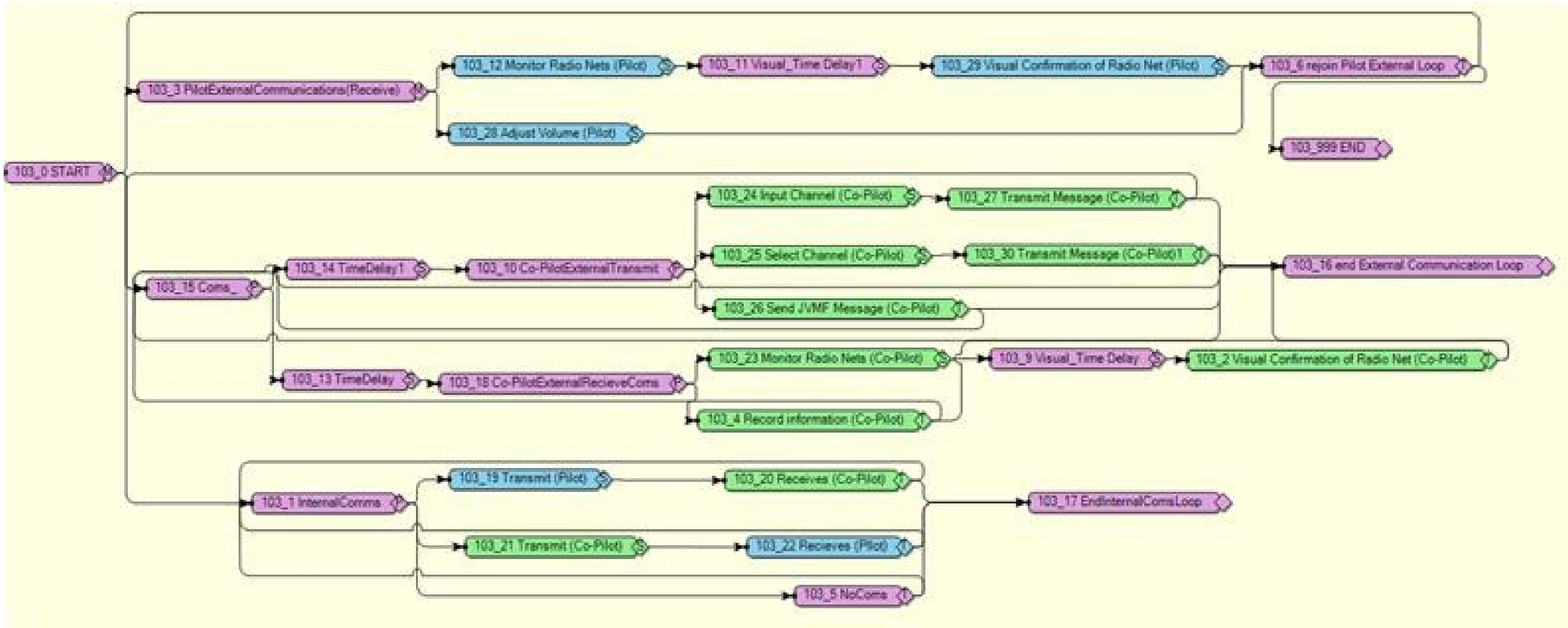


Figure 6. Communications Goal from the IMPRINT Model

The third part of the comms model is internal comms between the pilot and copilot. We learned from the pilot interviews and the ATM how critical communication is between the pilot and copilot. One pilot explained that if the cockpit is silent for more than 10 – 15 seconds, there isn't enough communication. Whenever either pilot is accomplishing a task, they verbally announce what they are doing. In Chapter II, we highlighted some examples of when internal communication should happen, primarily announcing actions with acknowledgement and directing and assisting. We modeled these interactions starting with task 103_1 Internal Comms. We assumed here that every time the pilot speaks, the copilot will respond, and vice versa. Each exchange includes a workload value for the listening and verbal response. We included a 10% probability that there were no communications to account for those times when there was nothing said, based on pilot interviews. The communication goal continues to loop until the model ends to reflect continuous communications throughout the mission.

e. Modifying the Model

Once we had a functioning model that depicted the flight tasks and task workload as described by the pilots, we used IMPRINT's reporting function to visualize that workload. We primarily used the operator workload detail report, the operator workload graph, and the operator overload report to review which tasks and combination of tasks caused workload spikes. The operator workload graph provides a visual depiction of the workload across one flight. We investigated anything that caused a workload spike over 60 on the graph and then analyzed the operator workload detail report to identify which tasks caused the spikes. The operator overload report quantitatively summarized the spikes and filtered the mission for any workload over 60, providing a quick reference for tasks to investigate. We ran the model 50 times to simulate different mission scenarios, ensuring we see nearly all combinations of tasks in the probabilistic nodes and their interactions. During this process, we identified a weakness in IMPRINT that only allows the software to generate results for viewing one run at a time.

Based on the results, we identified the combination of tasks that caused cognitive overload and investigated the feasibility of automating those tasks. To accomplish automation in IMPRINT, we changed the role of the tasks from the crewmember to an automated crew member, which removed the workload of that task from the pilot or copilot. Automation does not completely remove workload because the pilot must still monitor that task (Shivers 2021). When a task was automated, we added a pilot monitoring task to the model. Monitoring was assigned to either the pilot or copilot depending on who previously owned the task that was automated. We experimented with automation in different combinations until we eliminated significant workload spikes in the model. These automated tasks in the model serve as the recommendations for the HSA-DM team. Table 4 provides the list of communication tasks that caused cognitive workload spikes over 60 across 50 runs of the baseline model. We used this table to select five communication tasks to automate: monitor radio nets (pilot), adjust volume, input channel (copilot), select channel (copilot) and send JVMF message (copilot). While receive internal comms (pilot) had the most spikes above 60, we opted not to automate this task, because of how important internal communications are to the safety and operation of the aircraft. Likewise, transmitting messages is an essential task, and while it is possible to use presets, this is very mission dependent and cannot eliminate the need to transmit messages. Visual confirmation of radio nets is a monitoring task, and we therefore increased the frequency of this task to compensate for the automation. We decided not to automate Record Information (CoPilot) since this is a function pilots perform on their kneeboard and may want to maintain the ability to take manual notes. After eliminating those tasks from the automation list for the reasons provided, we began experimenting with shifting roles and including automation for the remaining five communication tasks associated with cognitive overload. These tasks are discussed in further detail in Chapter IV. To validate the feasibility of our recommendations, we also presented the model and our results to the pilots to garner feedback.

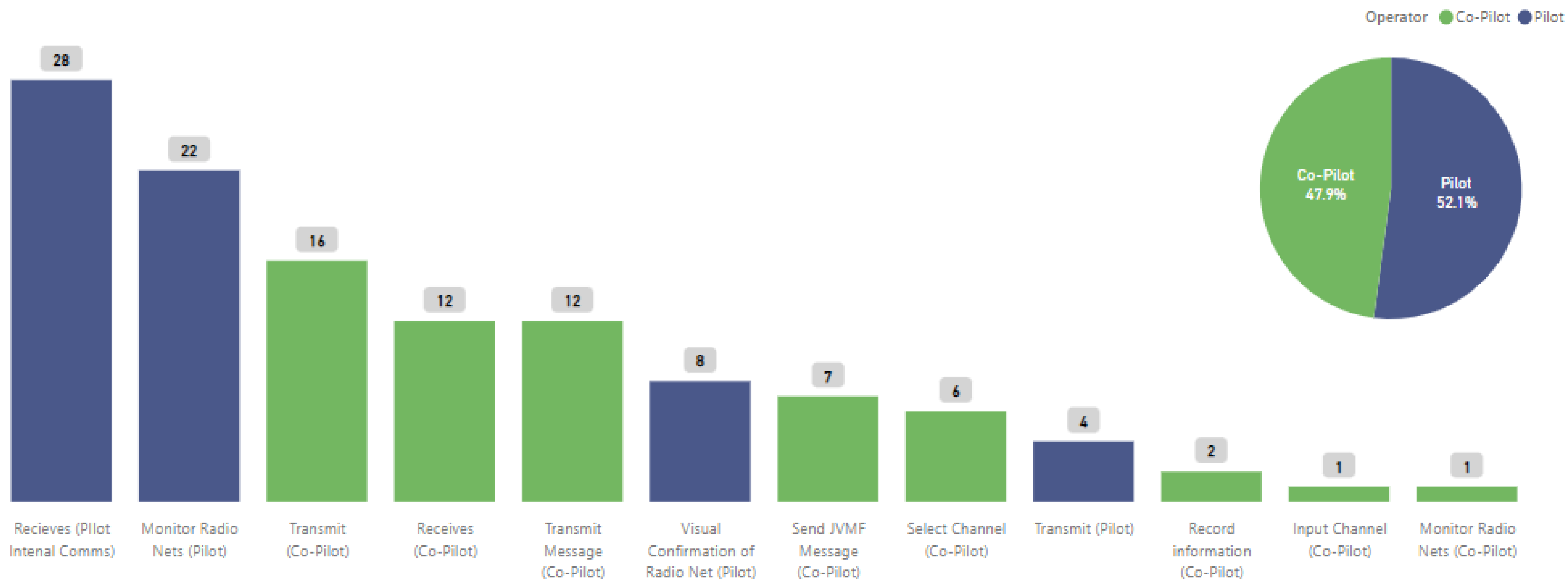


Figure 7. Baseline Workload Analysis: Communication Task

IV. RESULTS

A. OVERVIEW

Using the methods described in Chapter III, this research team generated multiple cognitive workload models. This chapter provides the key findings from the results and analysis of these models. Throughout this chapter, we provide the answers to the research questions in Chapter I:

- To what extent is a pilot's cognitive workload reduced if communication tasks are automated?
- How are communication tasks distributed between pilot, copilot, and an envisioned AI system?
- How does workload vary over the course of a particular phase of the MEDEVAC mission?

We found that automating communication tasks reduces cognitive workload with different levels of impact for the pilot and the copilot. Additionally, certain communication tasks, such as internal communications, must be maintained by the pilot and copilot to effectively operate the aircraft. Finally, cognitive workload fluctuates by frequency and degree of multitasking rather than time.

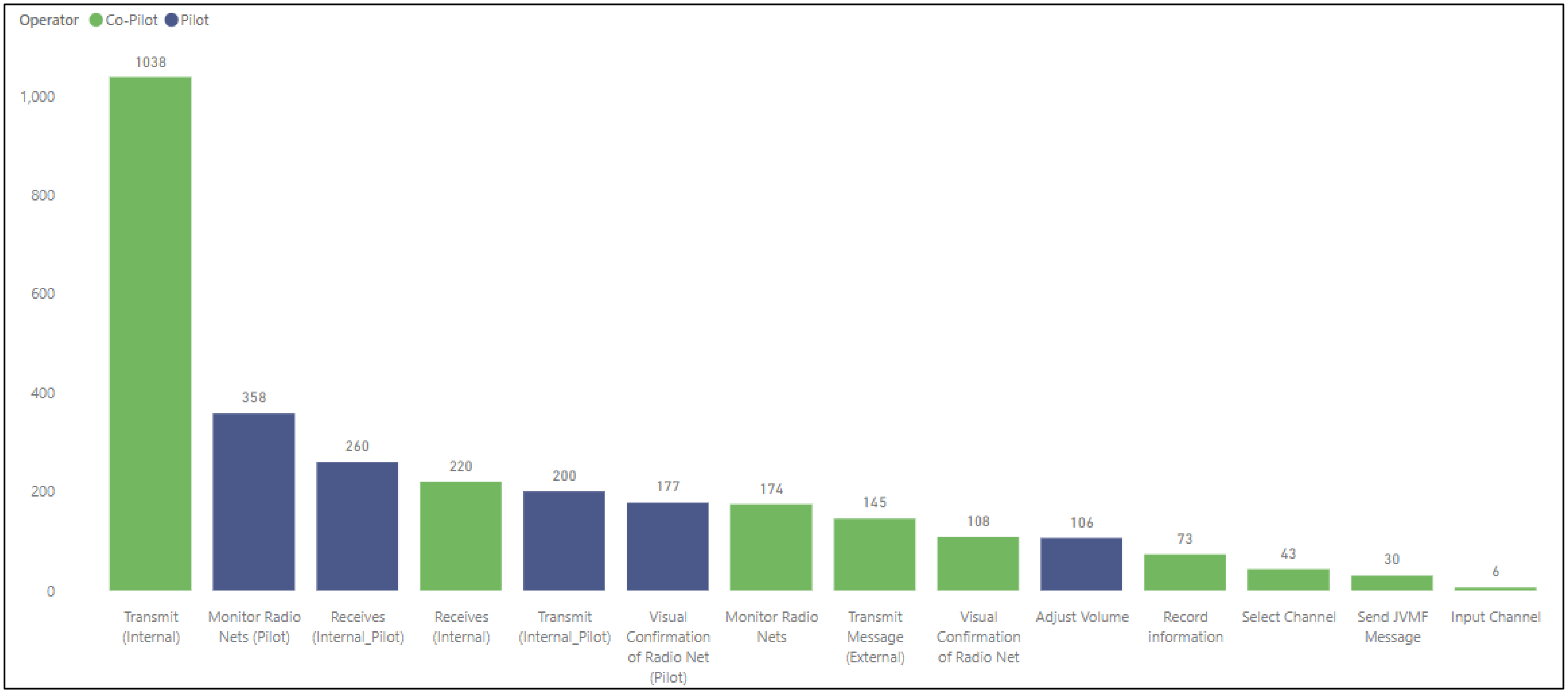
B. BASELINE MODEL

To address the primary research question, we developed a baseline cognitive workload model of a routine MEDEVAC flight based on the pilot interviews to which we could compare automation modifications. This is the model depicted in Chapter III. Figure 8 depicts the results of 50 runs of the baseline model. It portrays the frequency with which each of the communication tasks contributed to workload values over 60. We refer to each instance above 60 as a workload "spike." From these results, we identified six communication tasks that contributed to cognitive overload spikes:

- Monitor radio nets (pilot)

- Monitor radio nets (copilot)
- Input channel
- Select channel
- Send JVMF message
- Adjust volume

These are the tasks that we selected to automate. The justification for why we selected these tasks is described in Chapter III, section D.



This figure depicts the number of times individual tasks exceed workload threshold 60 across 50 trial runs of the baseline model

Figure 8. Baseline Model Results

C. AUTOMATED MODELS

The next step was to modify the baseline model by automating individual tasks, adding "monitor automation" tasks for those tasks, and analyzing the results. The individual modified models (see Appendix B) include four individual models with either one or two tasks automated, depending on whether they fall under the same overarching task. We modified the models in this way to analyze the effects of minor changes to the baseline model. We then incorporated all six changes into one final model to analyze the cumulative effect. Figure 9 depicts this final modified model. Each automated task is followed by a "Monitor AI" task to account for the pilots' cognitive workload as they monitor automation. We ran each individual model and the combined automation model 50 times each to assess the individual and cumulative effects of automation and to provide a large enough sample for analysis.

Figure 10 compares the total overload count between the baseline model and each individual modified model, along with the combined automation model. The overload count includes frequency of overload arising from all tasks, not just communication tasks, across 50 runs.

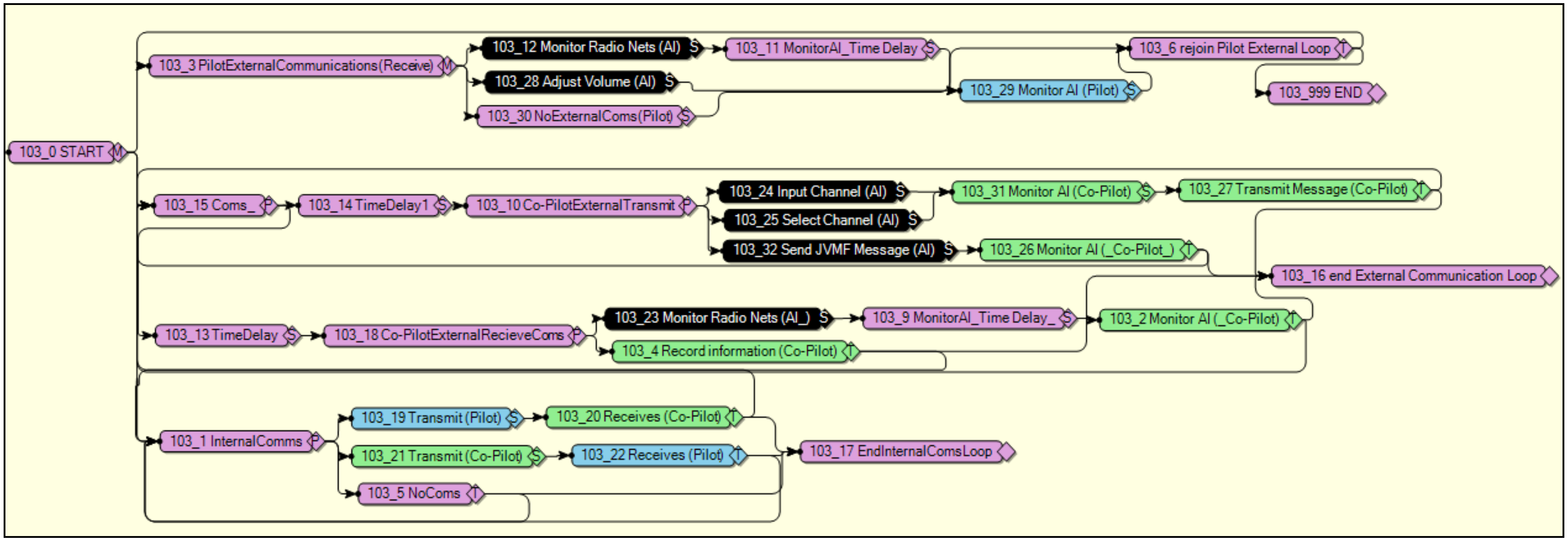


Figure 9. Baseline with Automation Model

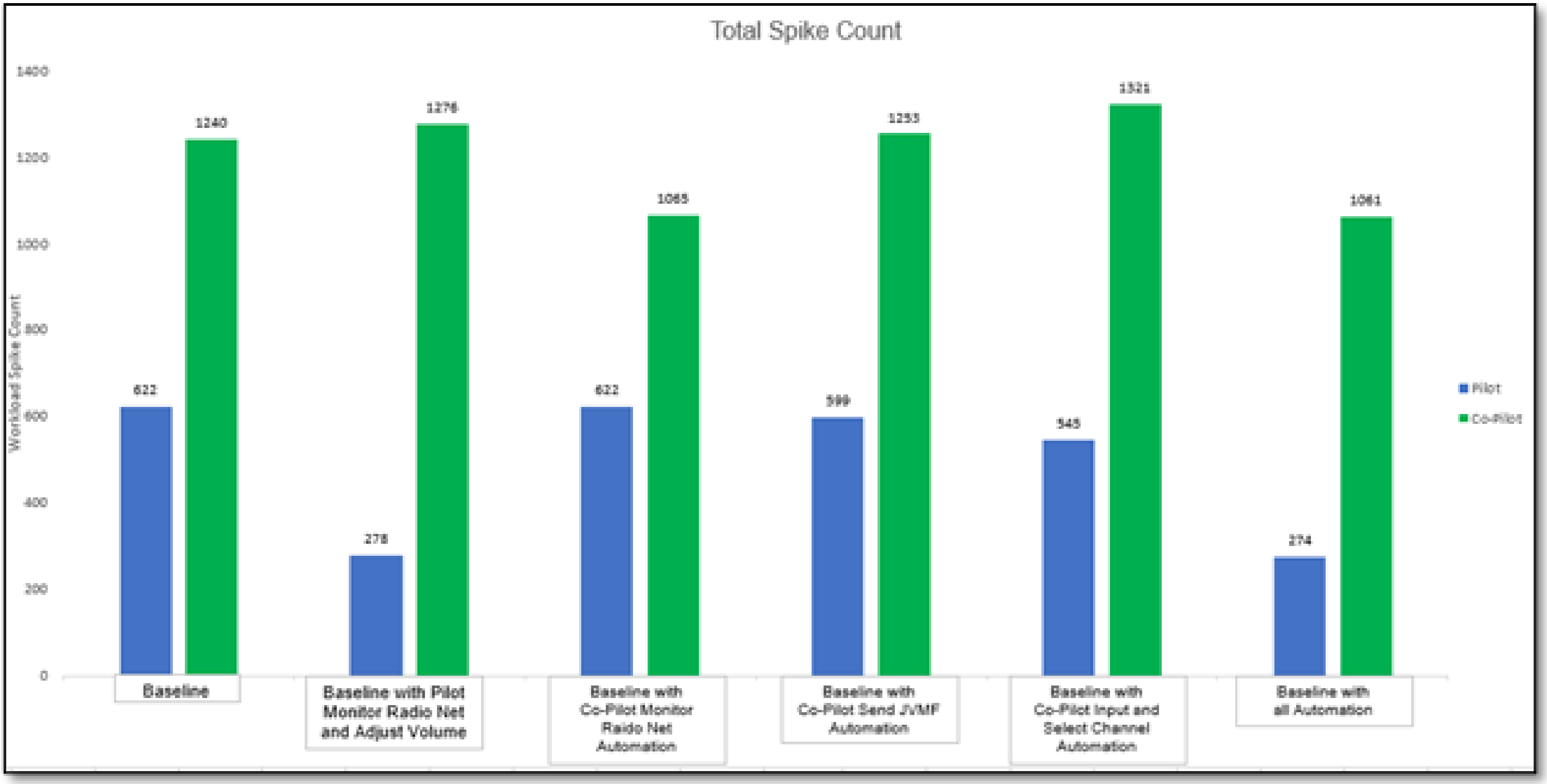


Figure 10. Overload Spike Count, All Models

Of these six tasks, automating external comms for the pilot (monitor radio nets and adjust volume) shows the most significant impact from automation, reducing the occurrence of pilot cognitive overload by 55%. Automating “monitor radio nets” for the copilot has the second most significant impact, reducing copilot overload spikes by 14.1%. The remaining three tasks do not have a significant impact. Automating “Send JVMF message” appears to increase copilot overload spikes by .01%, but this percentage is within the margin of error and not significant. Similarly, automating “input channel and select channel” appears to increase copilot overload spikes by .06%, which is also within the margin of error and not significant. Figure 11 depicts the baseline overload spikes compared to the combined model for the pilot and copilot.

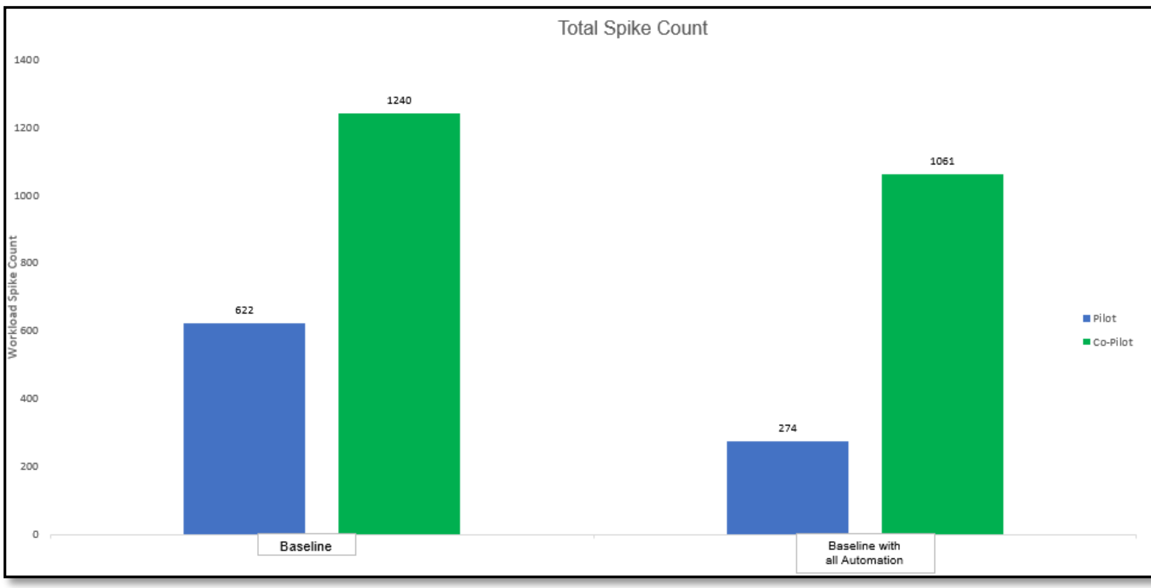


Figure 11. Pilot/Copilot Overload Spike Comparison, Baseline versus Combined Model

Figure 12 shows the total (combined pilot and copilot) workload difference between the unautomated and automated models. We see 572 fewer instances of net overload across 50 runs of the combined model. With all automation modifications incorporated, the pilot overload is reduced by 55.9%, the copilot overload is reduced by 14.4%, and total overload is reduced by 28%. Based on our analysis, the answer to the primary research question “To what extent is a pilot's cognitive workload reduced if communication tasks are automated" is approximately 56% for the pilot and approximately 14.5% for the copilot.

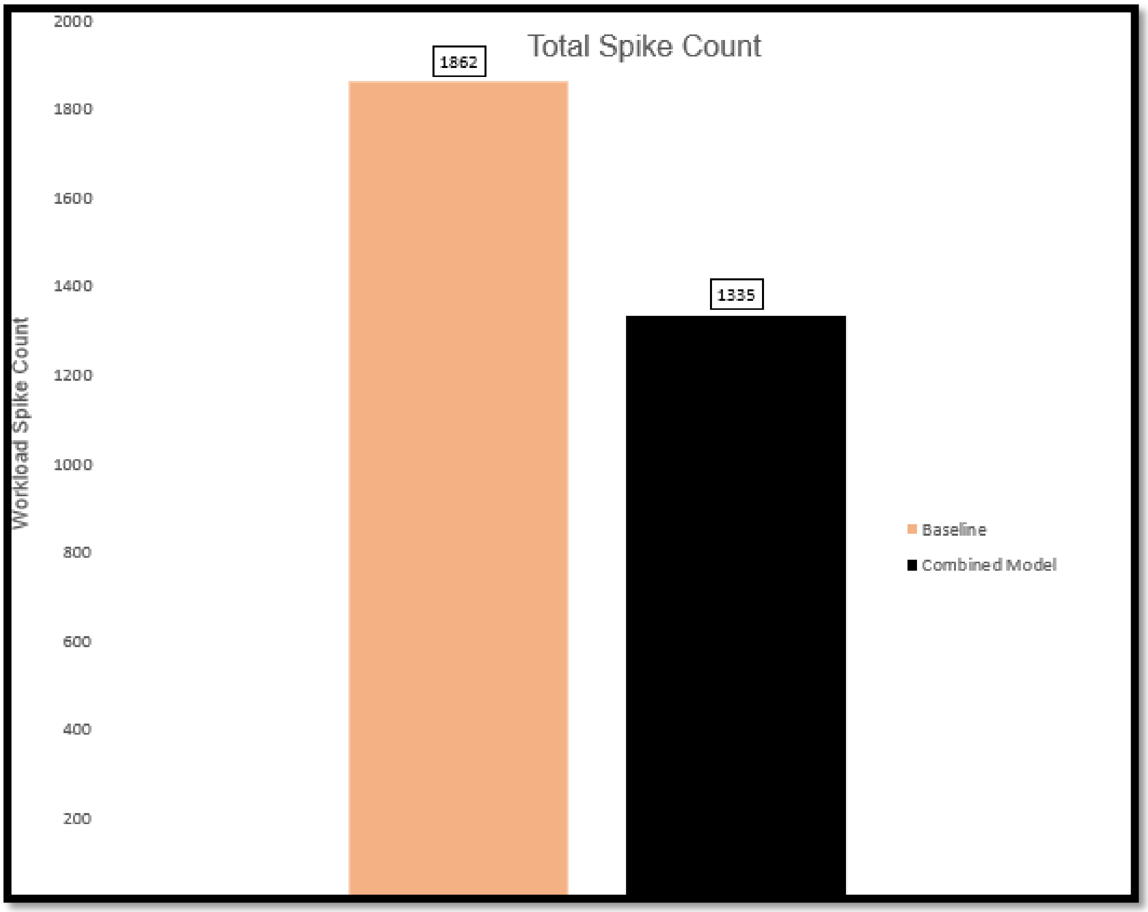


Figure 12. Total Overload Spike Comparison, Baseline versus Combined Model

To address the research sub-question "How are communication tasks distributed between pilot, copilot, and envisioned AI system?" we reviewed the roles assigned to the pilot, copilot, and automated system after the six tasks were automated in the combined model. This role distribution is shown in Figure 13, where the y-axis represents the total number of overload spikes across 50 model runs. The x-axis shows the comparison between baseline model and combined model. The pilot and copilot retain the internal communications functions and have additional tasks to monitor the automated system. The internal communication tasks contribute to cognitive overload frequently, however, as discussed in Chapter II, these tasks are essential to flight operations. For the pilot, AI monitoring is now the most frequent task that contributes to cognitive overload. The copilot also retains the tasks of transmitting messages externally and recording information. Even with these tasks being retained by the pilot and copilot, the overall workload for both operators decreased.

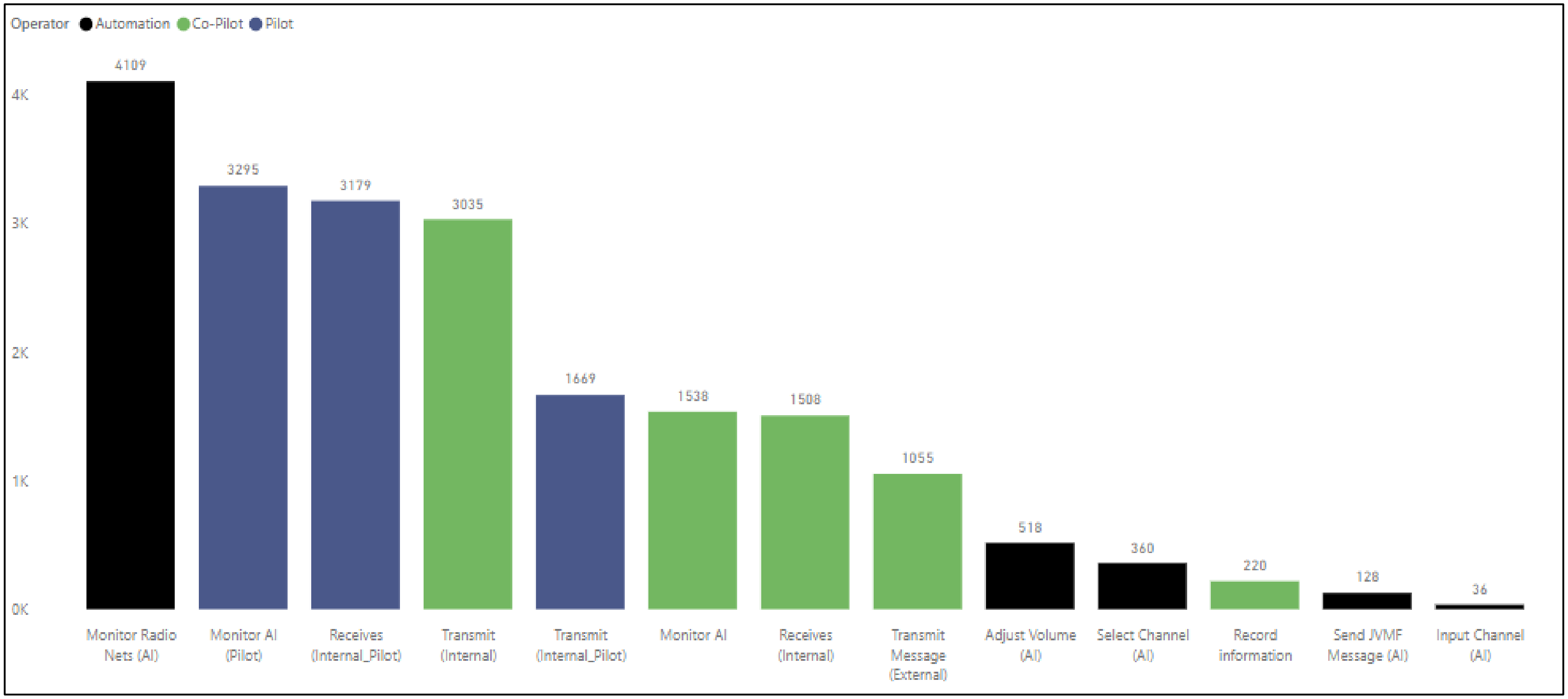


Figure 13. Distribution of Task

Figure 14 depicts the proportion of tasks conducted by the pilot and copilot for the baseline model. Figure 15 depicts the proportion of tasks for the combined automation model. Automation takes over about 25% of the tasks from the pilot and copilot, reducing pilot tasks by 20% and copilot tasks by 5%. This illustrates that by adding the six AI tasks, automation replaces a significant portion of tasks, removing the associated workload. This reinforces our findings in Figure 13.

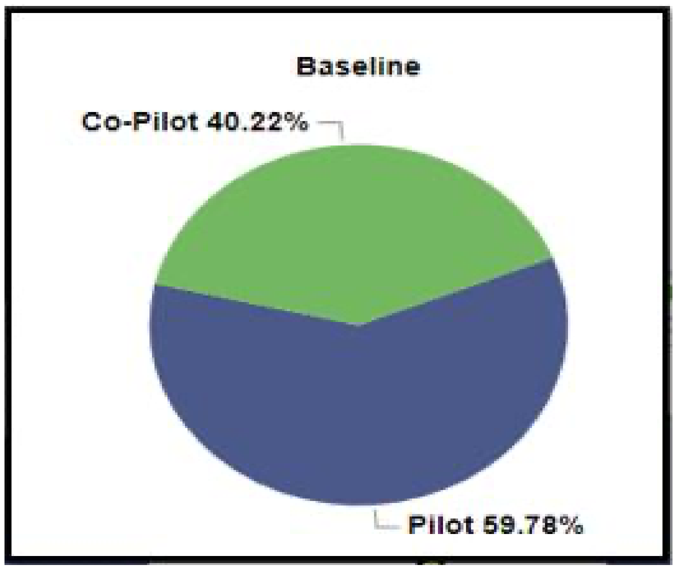


Figure 14. Task Proportion for Baseline

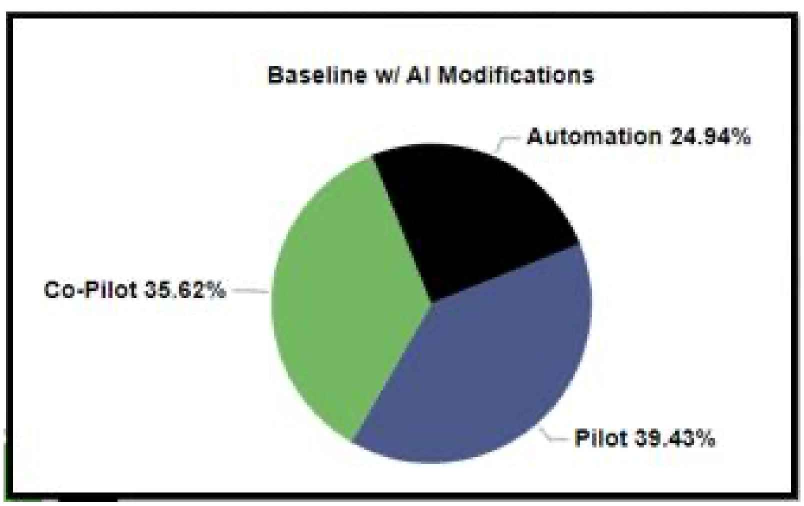


Figure 15. Task Proportion for Combined Model

To address the research sub-question "How does workload vary over the course of the enroute phase of the MEDEVAC mission?" we analyzed the graph of workload over time for individual baseline runs and compared the graph to the combined automation model graph. Figure 16 depicts an example of a workload graph for a single run of the baseline model, while Figure 17 depicts a workload graph for the same run within the combined automation model. Comparing the models, we see a decrease in overload spikes in the combined automation model, which is consistent with the results above. Additionally, the workload observed in the combined automation model is lower than the baseline model. This can be observed by looking at the y-axis difference between Figure 16 and Figure 17. Within the "enroute" phase of a MEDEVAC flight, workload is minimal until multiple tasks occur simultaneously, which is where the overload spikes occur. This breakdown is shown in Figure 18, which depicts the tasks associated with individual spikes of a single run. Because the tasks occur randomly based on the variation between flights, it is difficult to say that there is a pattern of workload variation within this phase of flight. Rather, workload varies based on how often pilots are multitasking. Future research should be conducted, however, to analyze and compare how workload varies between phases of flight.

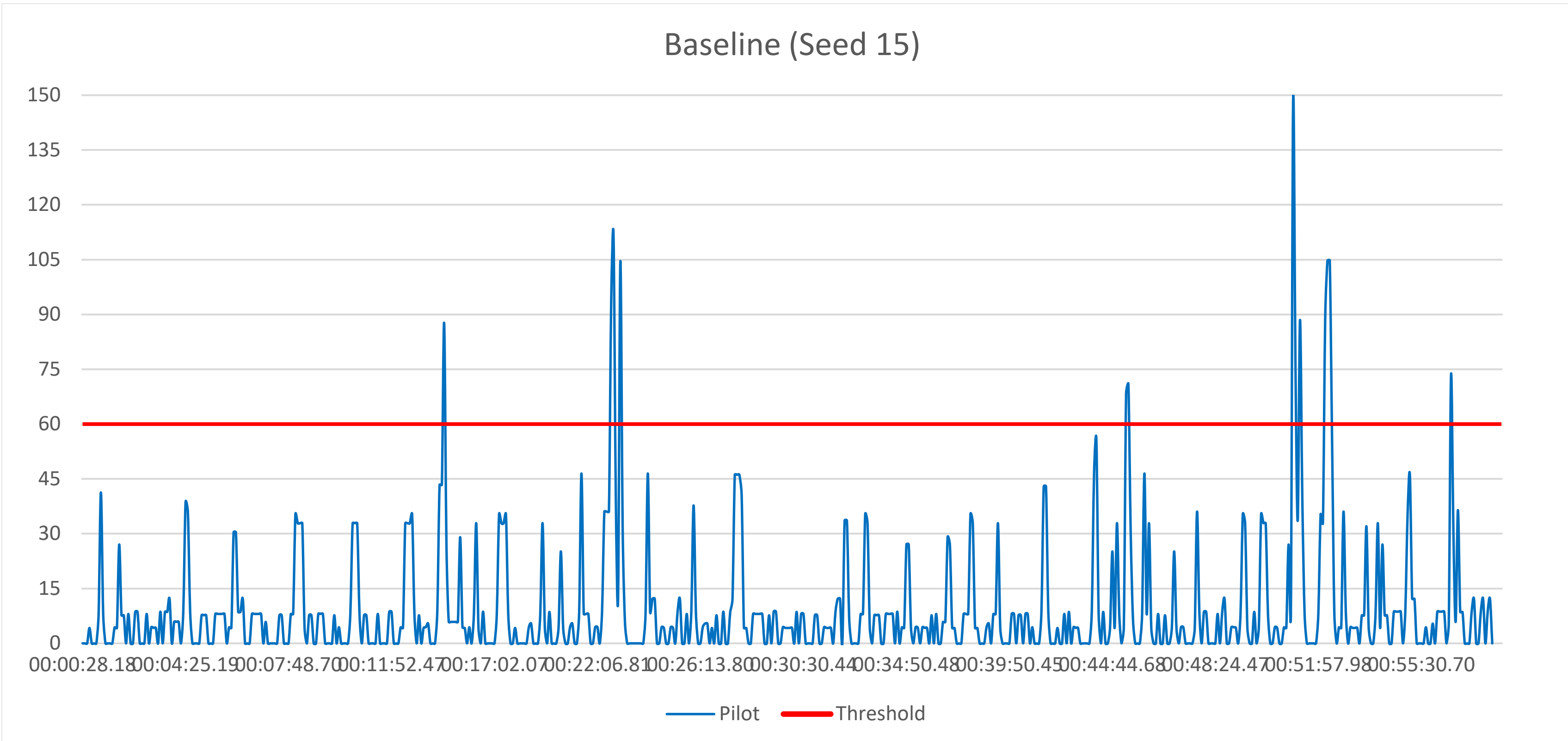


Figure 16. Individual Run Baseline Workload Graph

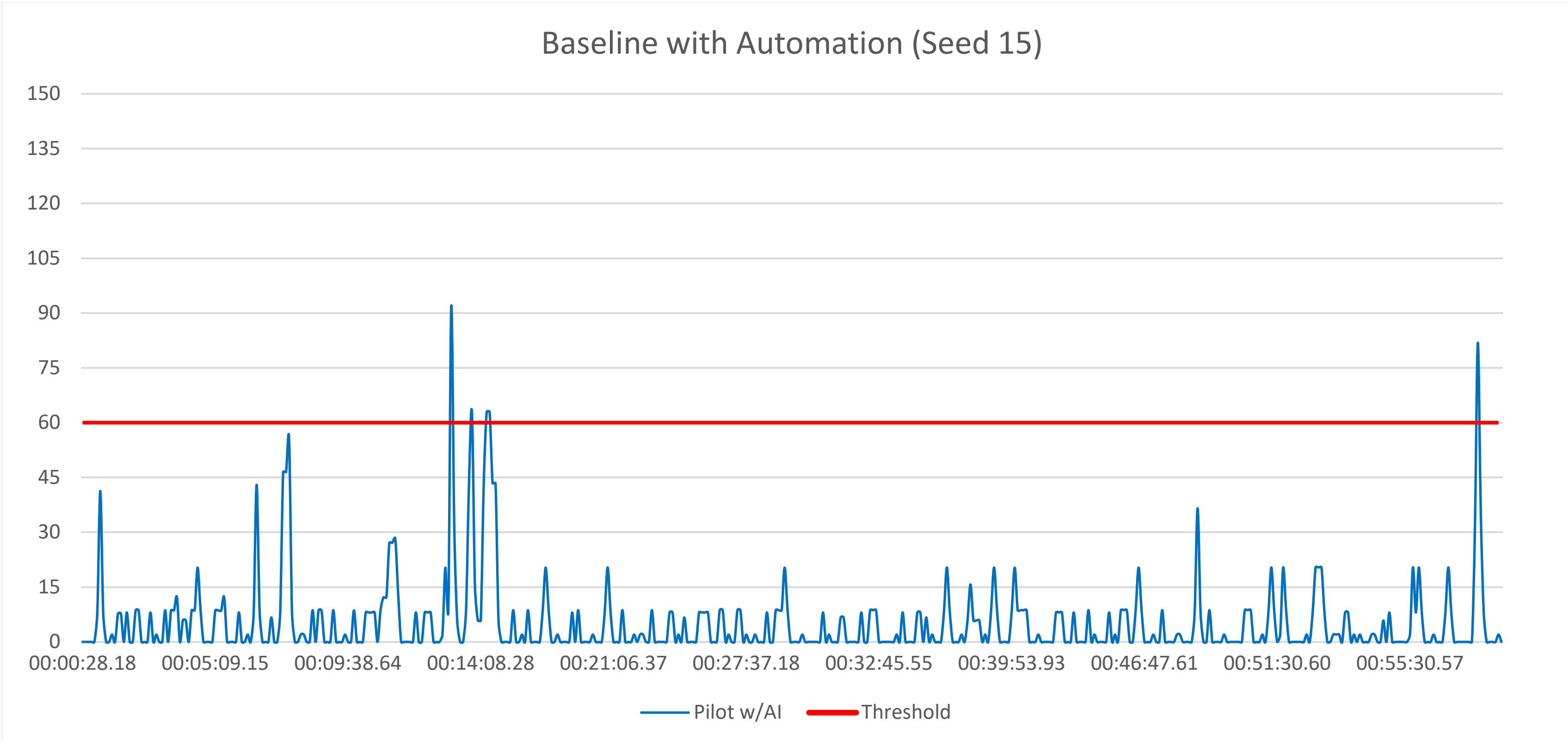


Figure 17. Individual Run Combined Automation Workload Graph

Table 4. Workload Spike Analysis

(HH:MM:SS.mm)	Operator	Function Name	Task Name	Overall Workload	Single Task Demand
0:05:35	Co-Pilot	(Root)	Fuel Management Procedures	86.495	7.28
0:05:35	Co-Pilot	Communications	Monitor Radio Nets	86.495	2.59
0:05:35	Co-Pilot	Communications	Transmit (Internal)	86.495	12.33
0:08:30	Co-Pilot	(Root)	Fuel Management Procedures	138.602	7.28
0:08:30	Co-Pilot	Communications	Record information	138.602	12.12
0:08:30	Co-Pilot	Communications	Transmit (Internal)	138.602	12.33
0:01:01	Pilot	(Root)	Scan Secondary Flight Display	7.69	7.69
0:01:46	Pilot	(Root)	Operate Cyclic Control	6.67	6.67
0:03:39	Pilot	Communications	Monitor Radio Nets (Pilot)	80.34	4.22
0:03:39	Pilot	Communications	Transmit (Internal_Pilot)	80.34	8.68
0:03:39	Pilot	Communications	Visual Confirmation of Radio Net (Pilot)	80.34	4.41
0:06:00	Pilot	(Root)	Operate Cyclic Control	81.08	6.67
0:06:00	Pilot	Communications	Receives (Internal_Pilot)	81.08	8.05
0:06:00	Pilot	Communications	Visual Confirmation of Radio Net (Pilot)	81.08	4.41
0:00:33	Co-Pilot	(Root)	Scan Primary Flight Display	5.92	5.92
0:01:21	Co-Pilot	Communications	Select Channel	4.28	4.28

D. SUMMARY

We successfully answered the primary and subordinate research questions by following the methods discussed in Chapter III. We analyzed the results of our baseline model to identify the six communication tasks that lend themselves to automation. Automating these tasks reduced pilot cognitive overload by 55.9%, copilot cognitive overload by 14.4%, and total cognitive overload by 28%, even after adding a supervisory task. The ANOVA analysis shown in Figure 19 highlights that the difference between crew workload between the two models is statistically significant, $F(1, 60478) = 102.92$, $p < .001$.

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Baseline	34623	258174	7.4567	8.2041
Automation	25857	199424	7.7126	11.032

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	968.77	1	968.77	102.92	3.6496E-24	3.8416
Within Groups	569274	60478	9.4129			
Total	570243	60479				

F The test is significant.
P-value Reject null hypothesis, which data shows a difference between the means.

Figure 18. ANOVA Comparison of Baseline Model versus Combined Model

The UH-60 ATM specified the importance of maintaining internal communications, therefore the pilot and copilot retain the internal communication tasks in our model. Similarly, our research revealed that the copilot should retain the freedom to transmit externally and take notes based on input from the pilot interviews. Finally, by analyzing individual runs of each model, we identified that workload fluctuations in this phase of flight occur randomly. Cognitive overload, however, is associated with the amount of multitasking conducted by either the pilot or the copilot.

V. DISCUSSION

A. OVERVIEW

Chapter IV provided the results that answer our research questions. In this chapter, we analyze these results, discuss our interpretations of them, and discuss the implications of these findings. Understanding individual task workload, sequencing, and timing when creating our model yielded interesting workload results that helped us identify which tasks may provide pilots the most relief if automated. This chapter explores these results further, discusses the limitations of our research, and discusses where this work could benefit from further study. Overall, the limitations and recommendations for further research generally revolve around the rapid timeline to complete the project. This led us to focus on a simpler phase of flight, without environmental and behavioral considerations included, providing significant opportunity for future research. Even so, our research is still beneficial. We have demonstrated how cognitively intensive flight operations can be, even during the simplest phase of flight, and how automation can be used to mitigate this workload. Additionally, single task automation seemed to create more workload for the copilot for specific tasks. This phenomenon highlights the fact that automation is not an easy button for solving overload problems. Automation must be targeted and deliberate, accomplishing the task in a way that is useful to the human operator while reducing overall workload.

B. PRIMARY RESEARCH QUESTION: TO WHAT EXTENT IS COGNITIVE WORKLOAD REDUCE IF COMMUNICATION TASKS ARE AUTOMATED?

We found that automation reduced total copilot overload from 1240 total overload spikes to 1061, a 14% decrease in overload spikes. Pilot overload spikes were reduced from 622 to 274, a 56% decrease. These results suggest that our method of identifying tasks to automate and assessing the effect of their implementation has potential for future use. One issue, however, is the increase in workload seen in Figure 10, in Chapter IV, for the copilot in models 2, 4, and 5. A possible explanation for why workload increased for the copilot in those models is that for each automated task, we assigned an associated AI monitoring task. This monitoring task represents the fact that automation is not as simple as giving tasks to a computer: the operator must still observe that the automation is producing the desired outcome. It is possible that monitoring automation takes more workload than simply completing the task manually. This finding reinforces what De Visser et al. (2008) found, as discussed in Chapter II. For simple or less frequent tasks such as adjust volume, input channel, and select channel, the workload created by those tasks was relatively small or occurred so infrequently that it did not contribute to many overload spikes. The workload associated with the smaller tasks was very similar to the workload created by the monitoring task, resulting in minimal impact to overall workload. This idea will be explored more in our limitations, but we believe these similar workload values could be due to the normalization process. We had a small sample size, and there were significant differences in VACP workload values elicited between pilots for many tasks. Therefore, the values we used may not have been precise enough to produce more significant differences in pilot workload when automation was added to the model.

C. SUB-QUESTION 1: HOW ARE COMMUNICATION TASKS DISTRIBUTED BETWEEN PILOT, COPILOT, AND ENVISIONED AI SYSTEM?

When we analyzed the frequency distribution of communications tasks performed before and after automation was implemented, we saw that monitor tasks became the most significant workload tasks for the pilot. Internal communications were the next most significant tasks for both pilots, as discussed in Chapter IV and seen in Figure 13. This finding aligns with the ATM's discussion on the frequency and importance of communication between the two crew members (Aviation Center of Excellence 2022). Additionally, the frequency of monitoring external nets by both crew members confirms HSA-DM's focus on communication as the best place to start implementing task automation (Shivers 2021). This finding also reinforces what Andrews et al. (2020) found in their study, that communication tasks greatly increase cognitive workload. Additionally, we analyzed the differences in proportions between the baseline and combined models as seen in Figure 14 and 15. Twenty five percent of tasks previously completed by the pilot and copilots were now completed by AI. This reduction in tasks for the pilot and copilot, results in an increase of spare cognitive capacity, which is one of HSA-DM's goals (Shivers 2021). This cognitive capacity can now be shifted to other tasks.

D. SUB-QUESTION 2: HOW DOES WORKLOAD VARY OVER THE COURSE OF THE ENROUTE PHASE OF THE MEDEVAC MISSION?

In Chapter IV, we explained how pilot workload is constantly changing as the mission progresses. Most of the time, combinations of one or two tasks do not exceed the cognitive workload threshold. Figure 18 depicts how single task demand is minimal, but when performed together, two or more tasks create overload well over the 60 threshold. Spikes being produced by simultaneous tasks is supported by Wickens' (2008) Multiple Resources Theory. Overall workload appeared to decrease over the course of the mission when automation was introduced to the model. On average, we saw the total spikes in a single run fall from six to four. Seeing this helps explain the decrease in total spikes across all 50 runs, which also helped answer our primary research question.

E. LIMITATIONS

The narrow scope of this project, and the challenging timeline we had available to complete our research, resulted in several limitations to our research. The following are areas that our research team may have included given more time, resources, and experience.

One limitation is that our model was developed to simulate the easiest phase of flight (routine flight after take-off and before landing). Some of our pilot interviews included remarks relating to ease of this phase. This fact helped us develop a basic model of flight, but it does not capture how workload varies during more complex activities such as hoist operations that include hover, or patient pickup. It also does not consider behavioral factors such as fatigue, emotional stress, or pilot experience. This model should serve as a good starting point for researchers who are interested in analyzing more complex flight scenarios.

Another key limitation is that the research group has no prior experience flying UH-60 helicopters or developing computer-based modeling. We worked hard to ensure that our task organization and model logic made sense and had our model verified by pilots and an IMPRINT SME. We recognize, however, that there may be flaws in parts of our approach in terms of our modeling or the manner in which we interpreted the pilots' explanations. There is likely room for improvement on this model from both perspectives.

Finally, our data was limited in two ways. First, we initially believed that interviewing six pilots would provide sufficient data to inform our task analysis. When we compared interview results to determine which values would be used in our model, we found more variance in the responses than expected. We suspect that this variance could be due to different levels of flight experience, different UH-60 models (L vs M), or their inexperience participating in a subjective feedback interview. Additionally, while we attempted to explain the concept of double accounting for workload and how it should be avoided, based on some of the results, we believe that some of the pilots did just that. In order to treat all data the same, we simply normalized all values rather than potentially adding bias by adjusting values that seemed unrealistic. A greater pool of interview subjects and more structured interviews could greatly refine the data. Second, we would have preferred to execute significantly more simulations than 50 runs. Originally, we believed 1,000 simulation runs would be ideal, enough to see every permutation of the model more than a few times. Unfortunately, IMPRINT is not built to provide more than one workload report at a time, making it very difficult to combine data for 1,000 simulations. We attempted using R scripts to help make up for this limitation but were unable to come up with a satisfactory solution. We discuss the potential for future research into issues like these in the next chapter.

F. SUMMARY

While there were limitations to our research, the results still are beneficial to the HSA-DM team. The results reinforce that their focus on communication tasks is warranted. Communication tasks significantly contribute to cognitive overload, and automation has the potential to reduce this overload and free up cognitive capacity for other tasks. Likewise, our research provides several opportunities for future studies.

VI. CONCLUSION AND RECOMMENDATIONS

A. OVERVIEW

The purpose of this project was to investigate how automation can be used to mitigate the pilot cognitive overload associated with communication tasks in a MEDEVAC scenario. This study has examined three research questions:

- To what extent is a pilot's cognitive workload reduced if communication tasks are automated?
- How can communication tasks be distributed between pilot, copilot, and the envisioned AI system?
- How does workload vary over a particular phase of a MEDEVAC mission?

To address these questions, we developed a baseline IMPRINT model to mirror and analyze the tasks involved in the "enroute" phase of MEDEVAC flight. We gathered the data to develop this model by reviewing scholarly literature and conducting cognitive walkthroughs and structured interviews with MEDEVAC pilots. The model was simulated several times to ensure that it resembled reality and was verified by pilots and an IMPRINT SME before analysis was conducted. We analyzed how specific communication tasks contribute to cognitive overload within this phase of flight and identified those communication tasks that contributed most to this overload. We developed multiple models automating various tasks and combination of tasks and assigned monitoring tasks for that automation to either the pilot or copilot. We ran each model 50 times and analyzed the results. Finally, we analyzed individual runs of the baseline and modified models to determine how workload varied across this phase of flight. We discovered that workload did not vary by time but rather by conditions when multitasking was warranted, which varies each flight.

Based on these findings, we developed recommendations for the HSA-DM team regarding what communication tasks should be automated to mitigate cognitive overload.

These automation recommendations include monitor radio tasks for both the pilot and copilot; adjust volume for the pilot; and input frequency, change frequency, and send JVMF message for the copilot. We also identified the communication tasks that should be retained by the pilot and copilot to effectively operate the aircraft, including internal communications for both pilots and external transmit and writing tasks for the copilot.

B. CONCLUSIONS

This research verified that both pilot and copilot cognitive workload is excessive at times during routine flight and that automation can mitigate some of this overload. This research also demonstrates that IMPRINT is an effective tool to model cognitive workload and to analyze how automation can be used to mitigate some of this workload. It also provides the HSA-DM team with a process to gain insight into similar issues with future research. This model can be used in other scenarios to develop automation suggestions.

The process for task analysis allowed us to elicit critical task information from the pilots. The variation between pilot description of the workload involved in various tasks indicated that pilots encounter different levels of workload for tasks based on their experience. The cognitive walkthrough demonstrated the value of using pilot experience rather than simply reviewing literature to gain an in-depth understanding of the tasks involved in flight. The literature did not adequately break the tasks down into subtasks to provide enough data to effectively model flight. By listening to the pilots describe their actions in real time as if they were flying, we were able to elicit subtasks that were crucial to our model.

The process of developing the model demonstrated the importance of leveraging SMEs. While we engaged in 24 hours of IMPRINT training, this training was not sufficient to provide the detailed knowledge required to develop the model. We spent over 20 hours consulting the IMPRINT SME to work through bugs in the model and learn IMPRINT techniques that were not covered in training. Developing the model also revealed the importance of using accurate VACP data to model cognitive workload. Unrealistic values caused significant spikes in workload, over 1,000, which did not accurately represent a routine MEDEVAC flight.

The baseline model revealed that communication tasks significantly contribute to cognitive overload spikes during routine flight. It also revealed a significant difference between pilot and copilot workload distribution. The copilot is far more cognitively taxed during routine flight. In scenarios where environmental conditions are not perfect, however, the pilot workload would likely increase, because their primary task is to fly the aircraft. The model can be modified to account for such conditions by increasing the VACP values and frequencies associated with the affected tasks. This would require additional pilot interviews to elicit accurate workload values for conducting tasks under those conditions.

Experimenting with automation in the modified models revealed that sometimes the task of monitoring AI can be more cognitively intensive than performing the automated task itself. Additionally, automating smaller tasks did not independently contribute significantly to workload reduction; however, cumulatively, the results were more impactful. Likewise, individual tasks that have higher workload values but are infrequent, such as send JVMF message and input channel, did not greatly contribute to cognitive overload. If conditions occur where frequency of these tasks is increased, they will likely have a more significant impact.

Finally, this project revealed several limitations within the built-in results analysis tools in IMPRINT. We had to use tools outside of IMPRINT, including Excel, Power BI, and data extraction codes, to conduct effective analysis of the model. While IMPRINT provides sufficient tools to analyze individual models, it does not support multiple runs of models. For future researchers using IMPRINT, being able to compile data with tools like Excel is essential to analyzing multiple runs of models.

C. RECOMMENDATIONS FOR HSA-DM

The six communication tasks in which cognitive workload can be mitigated through automation are:

- Monitor Radio Nets (pilot)
- Monitor Radio Nets (copilot)

- Adjust volume (pilot)
- Send JVMF message (copilot)
- Input channel (copilot)
- Change channel (copilot)

Automating these tasks in our model yielded a 28% combined reduction in cognitive overload. Pilot cognitive overload was reduced by almost 56%, while copilot cognitive overload was reduced by 14.4%. Additionally, while this analysis identified how automation can reduce cognitive workload, further research needs to be conducted on how to implement this automation. We therefore recommend that HSA-DM use this model and the processes for analysis and eliciting values from pilots to gather a larger sample of pilot feedback. This feedback will provide more input on workload values to produce a more accurate model.

D. RECOMMENDATION FOR FUTURE RESEARCH

The results of this project indicate that the IMPRINT model can be a useful tool in modeling various tasks and reporting the cognitive workload for specific operators, in our case the pilot and copilot. The reports and analysis conducted by this research team and the interviewees provided valid information on the communication tasks that would reduce overall cognitive workload through a routine flight.

While the data provided the necessary results, it was limited to input provided by six MEDEVAC pilots. Our first recommendation is to conduct this analysis again, but with a larger sample of MEDEVAC pilots to develop more accurate VACP values. Likewise, based on this additional data, more analysis needs to be conducted on how these automated tasks will be implemented using existing or future technologies.

Our second recommendation is to develop IMPRINT models and conduct analysis on additional scenarios, including the remaining phases of MEDEVAC flight and various environmental conditions, such as inclement weather and night flight. Additional scenarios could also account for crew members aside from the pilot and copilot. This model could also be modified to fit other aerial platforms.

Our third recommendation is to configure this data in a virtual simulation platform for validation. This validation would entail inputting the tasks that we identified for automation through a virtual simulation platform to allow the pilot and copilot to test and evaluate the new automated mechanics. This simulation would further examine the relationship between the operator and the automation. This information also could generate other information that IMPRINT cannot produce such as operator trust in automation, and the behavioral effects of the pilot such as fatigue.

We also recommend that, as material solutions for automation are developed, cost-benefit analysis should be conducted to determine if the benefits of automating certain tasks are worth the effort. We identified that when automating some tasks, the workload associated with the monitoring of the AI negated improvements or increased workload. This concept is something that must be investigated before physically implementing automation.

E. SUMMARY

Our research successfully answered the primary and subordinate research questions, which are nested in the goals and research focus areas of the HSA-DM program. The focus areas that our results inform are decreasing pilot workload and increasing spare cognitive capacity. More important than simply answering the questions, our research provides an affordable, repeatable process that can be applied to investigate workload associated with other tasks and platforms. Likewise, we are providing the HSA-DM team with a model that can be easily manipulated as a starting point for future research on the FVL. We recommend that feedback from additional pilots be incorporated to provide more accurate workload values to the model. Our model identified six tasks that contribute significantly to cognitive overload which can be mitigated by automation. HSA-DM now has a model that has been verified by an IMPRINT SME, supported by data from MEDEVAC pilots, and a process for investigating cognitive workload that has multiple applications.

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APPENDIX A. MODEL TASK DATA

Table 5. Model Task Data with VACP Values

Task	Function	Task	Audio	Cognitive	Fine Motor	Speech	Visual
0	(Root)	Model START					
1	(Root)	Manipulate Flight Controls					
10	(Root)	Operate Foot Pedals (Pilot)	0.5	1.54	1.3	0	2.53
100	(Root)	FVL_Movement					
101	(Root)	Movement_End					
103_0	Communications	START					
103_1	Communications	InternalComms					
103_10	Communications	Co-PilotExternalTransmit					
103_11	Communications	Visual_Time Delay1					
103_12	Communications	Monitor Radio Nets (Pilot)	1.59	0.5	0.69	1.44	0
103_13	Communications	TimeDelay					
103_14	Communications	TimeDelay1					
103_15	Communications	Coms_					
103_16	Communications	end External Communication Loop					
103_17	Communications	EndInternalComsLoop					
103_18	Communications	Co-PilotExternalRecieveComs					
103_19	Communications	Transmit (Pilot)	0.31	4.46	1.10	2.50	0.31
103_2	Communications	Visual Confirmation of Radio Net (Co-Pilot)	0.31	0.75	1.10	0.81	1.44
103_20	Communications	Receives (Co-Pilot)	4.16	4.36	2.13	0.81	0.50
103_21	Communications	Transmit (Co-Pilot)	2.06	3.66	3.23	2.88	0.50
103_22	Communications	Receives (Pilot)	3.84	3.59	0.00	0.31	0.31
103_23	Communications	Monitor Radio Nets (Co-Pilot)	1.78	0.50	0.00	0.31	0.00
103_24	Communications	Input Channel (Co-Pilot)	1.53	0.56	3.16	0.31	2.16
103_25	Communications	Select Channel (Co-Pilot)	0.31	0.75	1.10	0.31	1.81
103_26	Communications	Send JVMF Message (Co-Pilot)	0.31	1.63	0.69	0.31	0.94
103_27	Communications	Transmit Message (Co-Pilot)	0.31	1.85	2.13	0.31	1.50
103_28	Communications	Adjust Volume (Pilot)	0.69	0.75	3.16	0.31	0.50
103_29	Communications	Visual Confirmation of Radio Net (Pilot)	0.31	0.75	1.10	0.81	1.44
103_3	Communications	PilotExternalCommunications(Receive)					
103_30	Communications	NoExternalComs(Pilot)					
103_4	Communications	Record information (Co-Pilot)	2.06	3.44	2.99	1.25	2.38
103_5	Communications	NoComs					
103_6	Communications	rejoin Pilot External Loop					
103_9	Communications	Visual_Time Delay					
103_999	Communications	END					
104	(Root)	startComs					
11	(Root)	Scan Secondary Flight Display (Pilot)	0.5	2.49	0.31	0	4.39
12	(Root)	Scan Primary Flight Display (Pilot)	0.5	2.49	0.31	0	4.39
13	(Root)	Scan External Environment (Pilot)	0.5	2.49	0	0.31	5.31
14	(Root)	Identify Obstacles (Pilot)	0.31	3.29	1.93	1.19	5.5
15	(Root)	Scan Primary Flight Display(Co-Pilot)	0.5	2.16	0	0	3.26
17	(Root)	Scan External Environment(Co-Pilot)	0.5	2.8	0	0.31	5.13
18	(Root)	Identify Obstacles(Co-Pilot)	0.31	3.48	0	0.81	5.31
2	(Root)	instrumentScanFreq					
5	(Root)	Fuel Management Procedures (Co-Pilot)	0	2.52	2.44	0.63	1.69
59	(Root)	Conduct Evasive Manuevers (Pilot)	1.69	3.85	1.79	1.69	3.94
67	(Root)	Operate Collective Control (Pilot)	0.69	0.75	2.41	0.31	2.53
75	(Root)	Initialize Model Conditions					
77	(Root)	Operate bezel keys (Co-Pilot)	0.31	2.58	2.54	0	2.39
78	(Root)	Operate the multifunction slew controller (MFSC,Co-Pilot)	0.31	2.58	3.16	0.63	2.5
79	(Root)	Operate the collective cursor slew controller (Co-Pilot)	0.31	2.58	3.16	0.63	2.39
86	(Root)	rejoinAviateLoop					
87	(Root)	pilotSwitch					
88_0	ShiftAnnouncement	START					
88_10	ShiftAnnouncement	Operate Cyclic Control (Co-Pilot)	0.5	1.54	2.1	0	2.53
88_11	ShiftAnnouncement	Operate Multifuncational Display (Pilot)					
88_12	ShiftAnnouncement	Pilot focus internal to the cockpit	0.5	1.63	0.81	1.19	1.75
88_13	ShiftAnnouncement	End Pilot Shift Internal					
88_14	ShiftAnnouncement	FVL_Movement					
88_15	ShiftAnnouncement	Movement_End					

88_3	ShiftAnnouncement	airspaceSurvFreq(Co-Pilot)					
88_4	ShiftAnnouncement	Scan External Environment(Co-Pilot)	0.50	2.49	0.00	0.31	5.31
88_5	ShiftAnnouncement	Identify Obstacles(Co-Pilot)	0.31	3.29	1.93	1.19	5.50
88_6	ShiftAnnouncement	Manipulate Flight Controls					
88_7	ShiftAnnouncement	Operate Foot Pedals (Co-Pilot)	0.5	1.54	1.3	0	2.53
88_8	ShiftAnnouncement	Operate Collective Control (Co-Pilot)	0.69	0.75	2.41	0.31	2.53
88_9	ShiftAnnouncement	rejoinAviateLoop					
88_999	ShiftAnnouncement	END					
9	(Root)	Operate Cyclic Control (Pilot)	0.5	1.54	2.1	0	2.53
90	(Root)	end other Tasks					
92	(Root)	Manage Flight Operations (Co-Pilot)					
94	(Root)	end other Tasks1					
96	(Root)	Operate Digital Map (Co-Pilot)					
999	(Root)	Model END					

APPENDIX B. ILLUSTRATION OF ALL SIX MODELS USED FOR ANALYSIS

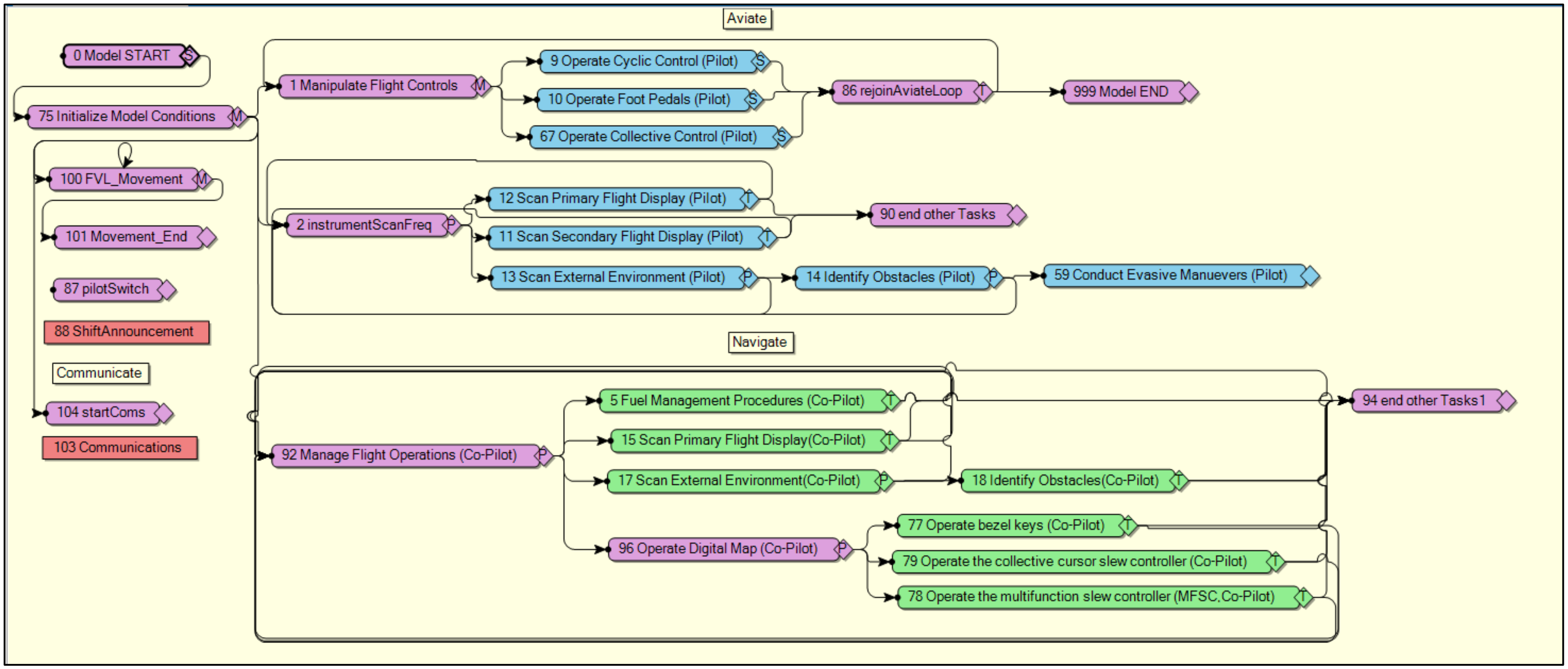


Figure 19. Base Model with Aviate and Navigate Tasks Shown. Aviate and Navigate Was not Changed throughout the Six Different Models, Only Communication was Adjusted

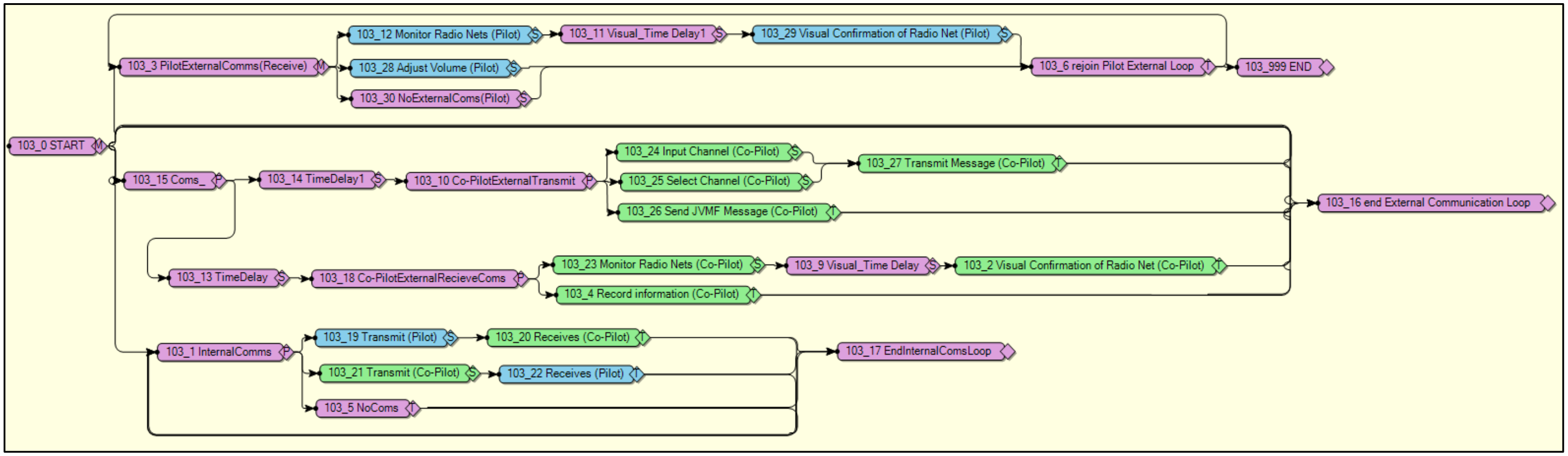
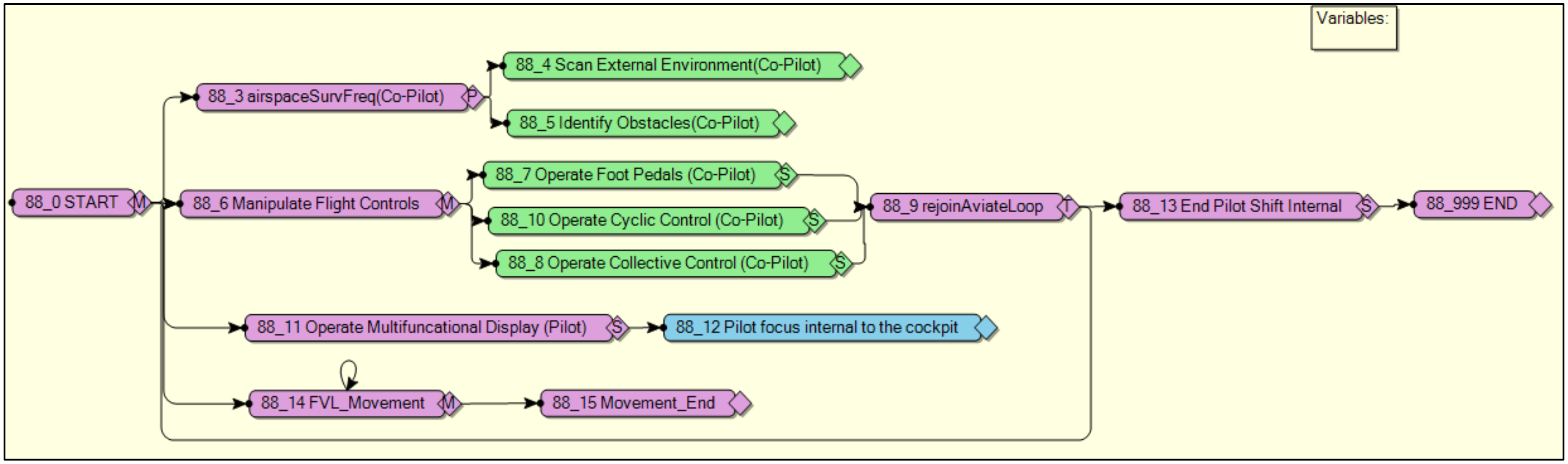
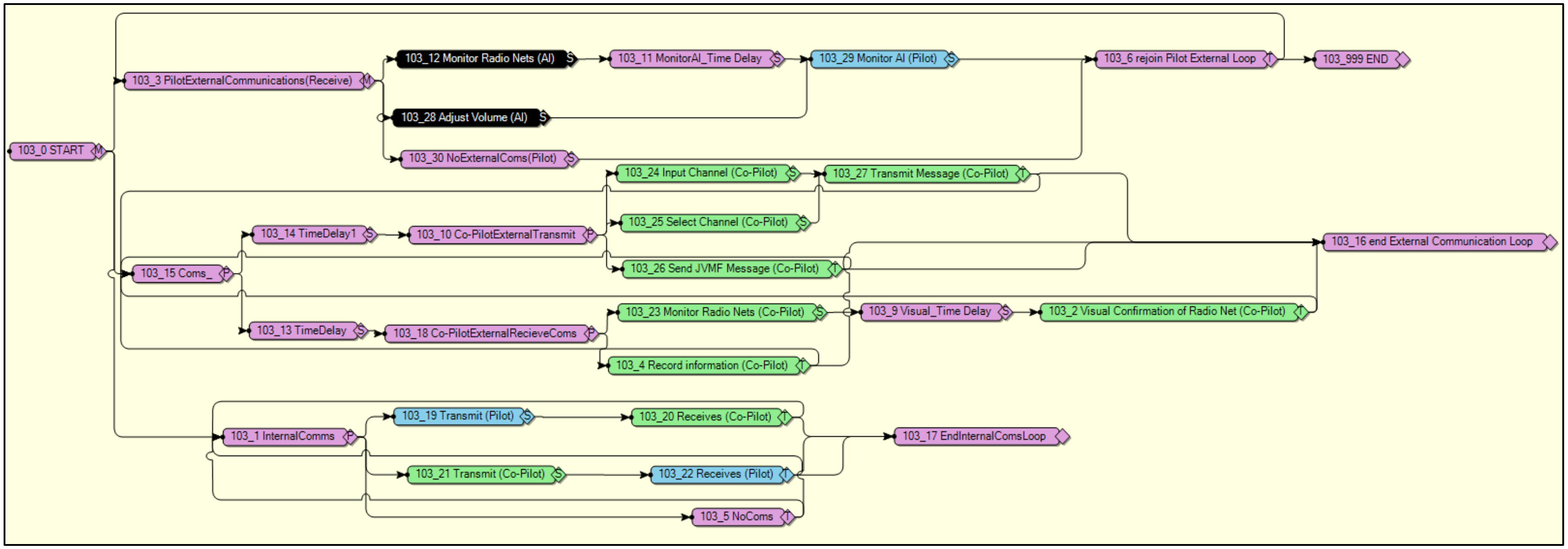


Figure 20. Communication Goal Expanded for Baseline Model



This is the expanded Pilot Shift Internal goal. This was designed to simulate the times the pilot needed to focus on something other than flying and the co-pilot had to take over flight responsibilities. The Variables box seen in the upper right was a troubleshooting tool used during model development.

Figure 21. Pilot Shift Internal Goal Model



Observe the monitor AI task assigned which assigns a small ammount of visual and cognitive workload to ensuring AI properly executes these tasks.

Figure 22. Communicate Goal with Pilot's Monitor Radio Nets and Adjust Radio Volume Automated

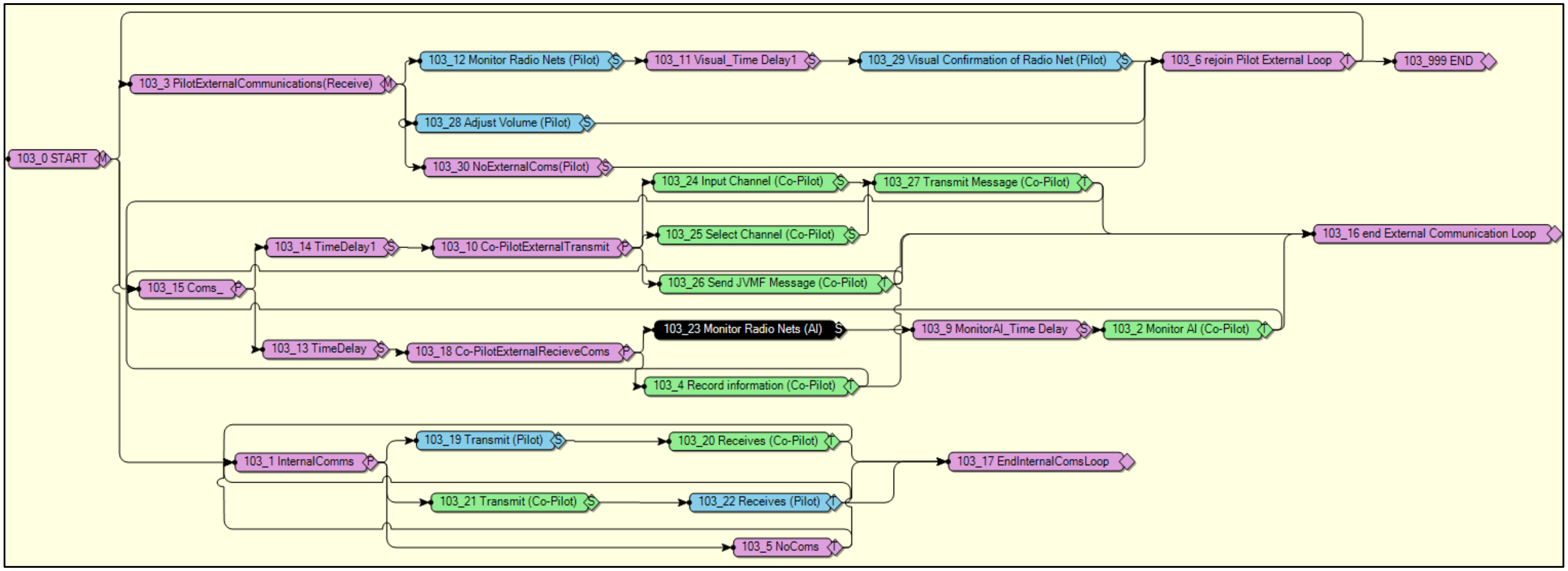


Figure 23. Communicate Goal with Copilot's Monitor Radio Nets Automated

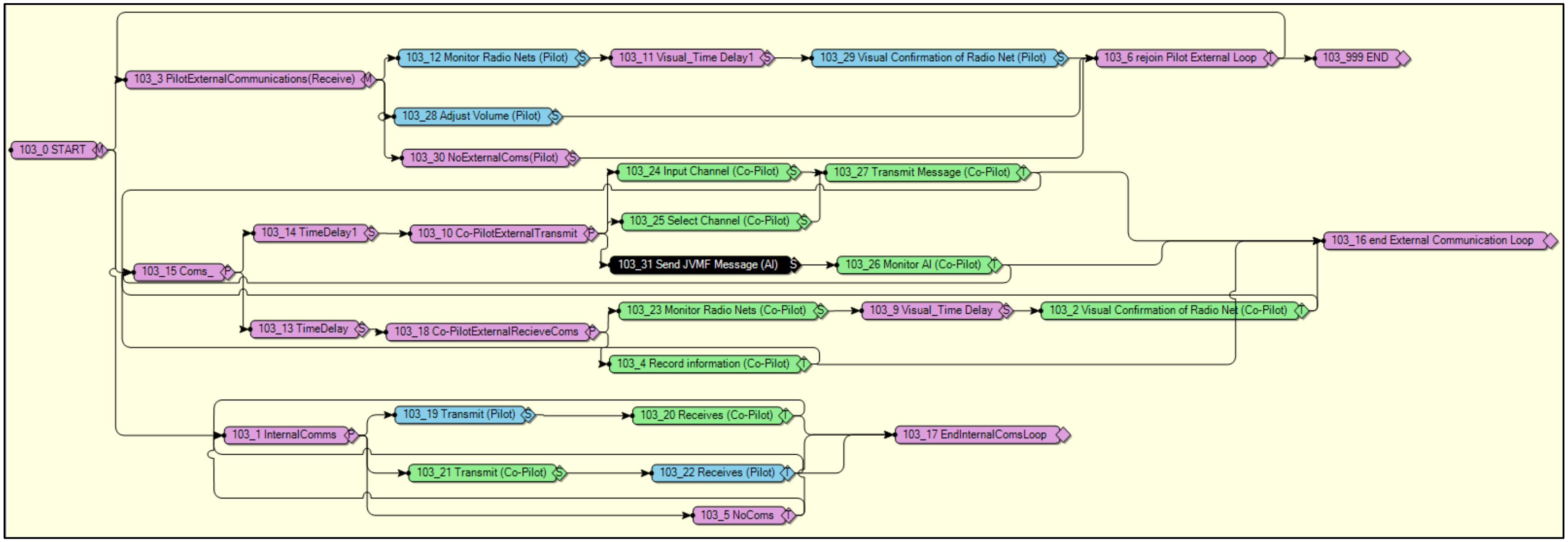


Figure 24. Communicate Goal with Copilot's Send JVMF Message Automated

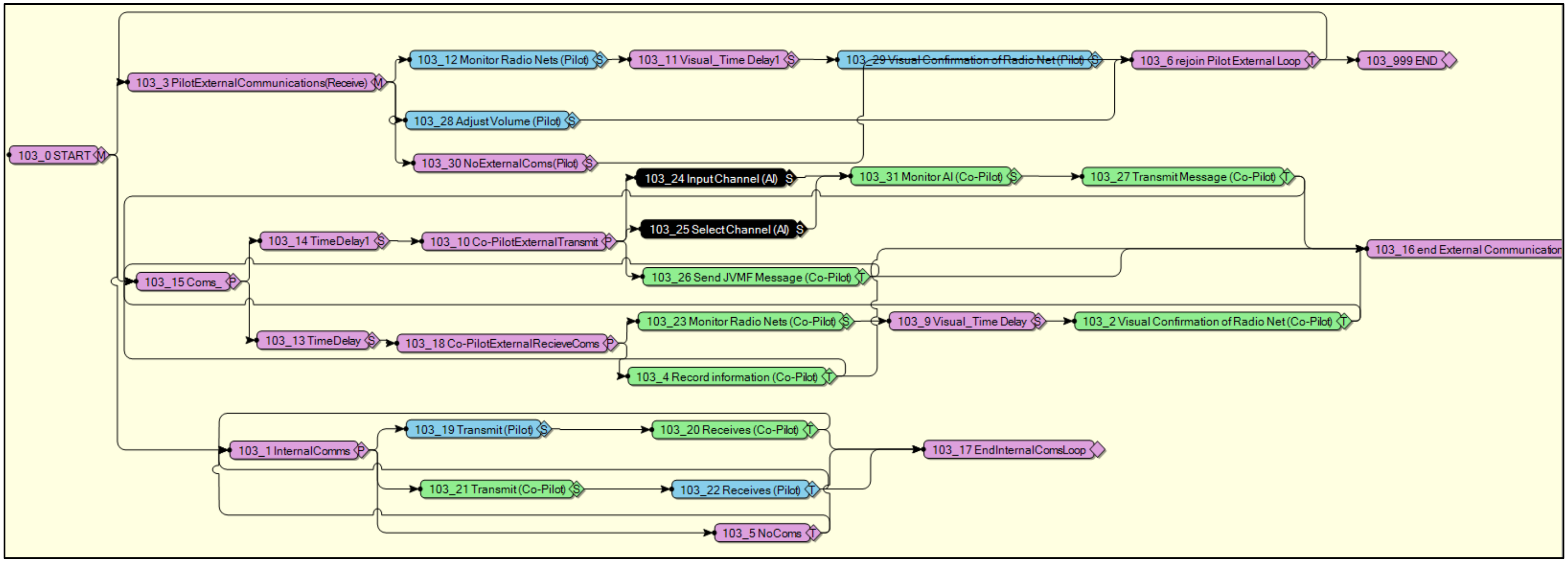


Figure 25. Communicate Goal with Copilot's Input Channel and Select Channel Automated

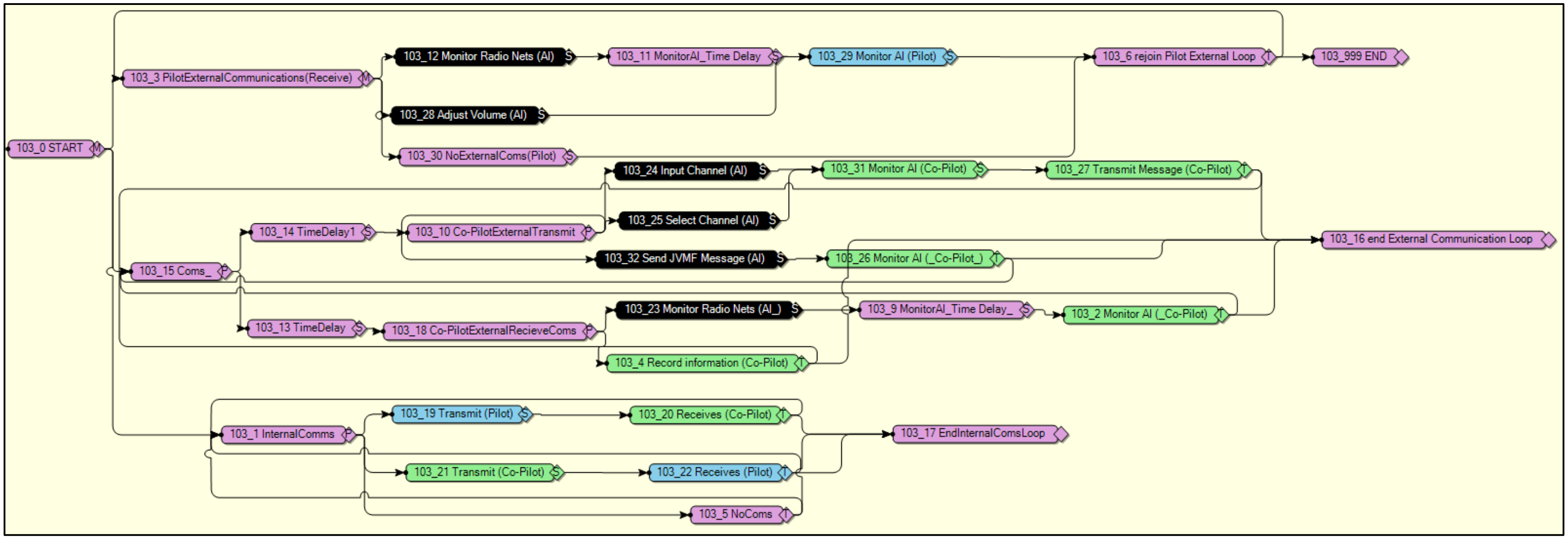


Figure 26. Communicate Goal with All Six Tasks Automated at Once

APPENDIX C. TASK ANALYSIS DATA

Table 6. Consolidated Task Analysis Data

High Level Task	Operator	Task	Sub-task	Sub-sub task	Auditory				Cognitive				Fine Motor				Speech				Visual			
					B	M	P	W	B	M	P	W	B	M	P	W	B	M	P	W	B	M	P	W
Aviate	Pilot	Manipulate Flight Controls	Operate Cyclic		1	1	0	0	1.2	1	1	2.6	3.6	2.6	2.6	0	0	0	0	0	1	3	1.5	4.4
			Operate Foot Pedals		1	1	0	0	1.2	1	1	2.6	0	2.6	2.6	0	0	0	0	0	1	3	1.5	4.4
			Operate Collective		1	1	0	1	1.2	1	1	0	3.6	2.6	2.6	1	0	0	0	1	1	3	1.5	4.4
		Instrument Scans																						
			Scan Primary Display		0	1	0	1	4.6	4.6	1	0	0	0	0	1	0	0	0	0	4	6	3	4.4
			Scan Secondary Display		0	1	0	1	4.6	4.6	1	0	0	0	0	1	0	0	0	0	4	6	3	4.4
		Airspace Surveillance																						
			Scan External Environment		0	1	0	1	4.6	4.6	1	0	0	0	0	0	0	0	0	1	5	6	6	4.4
			Identify Obstacles		0	1	0	0	5	4.6	4.6	0	4.6	2.6	0	0	0	2	2	1	6	6	6	4.4
	Copilot			Conduct Evasive Mvrs	0	2	0	4.2		4.6	6.8	4.6		2.6	2.6	2.6		2	2	1		6	6	5
		Instrument Scans																						
			Scan Primary Display		1	1	0	0	1.2	4.6	1	1	0	0	0	0	0	0	0	0	1	5	3	4.4
			Scan Secondary Display		1	1	0	1	1.2	4.6	1	1	3.6	0	0	0	0	0	0	0	1	5	3	4.4
		Airspace Surveillance																						
			Scan External Environment		0	1	0	1	4.6	4.6	1	1	0	0	0	0	0	0	0	1	5	5	6	4.4
			Identify Obstacles		0	1	0		4.6	4.6	4.6	1	0	0	0	0	0	0	2	1	6	5	6	4.4
		Manage Flight Ops																						
			Fuel Management Procedures		0	0	0	0	5.3	4.6	0	0	6.5	2.2	0	0	0	2	0	0	3	3	0	1
Navigate	Pilot/Copilot	Announce shift internal			0	1	0	1	0	4.6	0	1	0	2.6	0	0	2	2	0	1	0	5	0	1
		Operate Digital Map	Operate bezel keys on the MFD		0	1	0		0	4.6	0	5.5	2.2	5.5	0	2.2	0	0	0	0	0	5	0	4.4
			Operate the collective slew controller		0	1	0	0	0	4.6	0	5.5	5.5	5.5	0	2.2	0	2	0	0	0	5	0	4.4
			Operate the multifunction slew controller (MFSC)		0	1	0	0	0	4.6	0	5.5	5.5	5.5	0	2.2	0	2	0	0	0	5	0	5
Communicate	Pilot		Transmit Information		0	1	0		1.2	4.6	7	5.5	2.2	0	2.2	0	4	2	3	1	0	1	0	0
			Receive Information		6	6	4.5	0	1.2	4.6	7	1	0	0	0	0	0	0	0	1		1	0	0
		External Communications																						
			Monitor Radio Nets		0	1	4.5	0	0	1	0	1	0	2.2	0	0	4	0	0	1	0	0	0	0
			Visual Confirmation of Channel		0	1	0	0	0	1	1.2	1	0	2.2	2.2	0	0	2	0	1	0	1	4	0
			Transmit Information (Radio)		0	6	0	1	1.2	5	7	1	2.2	2.2	2.2	0	0	4	3		0	1	0	
			Input Radio Freq		0	6	0	1	0	5	0	1	5.5	2.2	5.5	5.5	0	4	0	1	1	1	5.1	1
			Adjust Volume	Identify which channel is transmitting	0	1	1	1	0	1	1.2	1	5.5	2.2	5.5	0	0	0	0	1	1	0	1	0
	Co-Pilot	Internal Communications																						
			Transmit Information		0	6	0	1	1.2	5	7	1	2.2	2.2	2.2	5.5	4	4	3	1	0	1	0	1
			Receive Information		6	6	4.5	1	1.2	5	7	4.6	0	2.2	0	5.5	0	2	0	1	0	1	0	1
		External Communications																						
			Monitor Radio Channels		0	1	4.5	1	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0
			Select Radio Channel for transmition		0	0	0	1	0	1	1.2	1	0	2.2	2.2	0	0	0	0	1	0	3	4	0
			Transmit Information (Radio)		0	3	0	1	1.2	4.6	7	1	2.2	2.2	2.2	0	4	2	3	1	3	1	0	0
			Input Radio Freq		0	4.3	0	1	0	1.2	0	1	5.5	2.2	5.5	0	0	0	0	1	0	3	5.1	0
				Identify which channel is transmitting		1	1	1		1	1.2	1		2.2	0	5.5	0	0	0	1	0	0	0	1

[redacted]	Monitor JVMF	[redacted]	0	0	No input, flew UH-60L, didn't have capability	1	4.6	N/A	N/A	1	2.2	N/A	N/A	0	0	N/A	N/A	1	3	N/A	N/A	0
	Send Message		0	0		1	4.6	1.2		1	5.5	2.2		0	0	0		1	3	3		0
	Receive Message		0	1		1	4.6	4.6		4.6	2.2	2.2		5.5	0	0		1	3	3		1
	Adjust Volume			1		1		1		4.6		2.2		5.5	0	0		1	0	0		1
	Record Information		0	6		1	4.6	4.6		5.5	5.5	4.6		2.2	0	4		0	3	3		4

LIST OF REFERENCES

Andrews, Jinan M., Christina F. Rusnock, Michael E. Miller, and Douglas P. Meador. 2020. "Reshaping Airpower: Development of an Imprint Model to Analyze the Effects of Manned-Unmanned Teaming on Operator Mental Workload." In *2020 Winter Simulation Conference (WSC)* 170–81. https://doi.org/10.1109/WSC48552.2020.9383859.

———. 2020b. "Human Performance Modeling: Analysis of the Effects of Manned-Unmanned Teaming on Pilot Workload and Mission Performance." Master's Thesis, Air Force Institute of Technology. https://scholar.afit.edu/etd/3225

Bierbaum, Carl R., Sandra M. Szabo, and Theodore B. Aldrich. 1988. Task Analysis of the UH-60 Mission and Decision Rules for Developing a UH-60 Workload Prediction Model. Volume 4. Segment Decision Rules Appendixes H and I. Report Number – ASI690-302-87. Fort Rucker, AL: U.S. Army Research Institute Aviation Research and Development Activity. https://apps.dtic.mil/sti/citations/ADA201317.

Billings, C. E. 1991. "Human-Centered Aircraft Automation: A Concept and Guidelines." Official memorandum. Moffett Field, CA: National Aeronautics and Space Administration Ames Research Center. https://ntrs.nasa.gov/search.jsp?R=19910022821.

Chen, Fang, Jianlong Zhou, Yang Wang, Kun Yu, Syed Z. Arshad, Ahmad Khawaji, and Dan Conway. 2016. *Robust Multimodal Cognitive Load Measurement*. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-31700-7

Carter, Matthew W., Greg Griffith, Pete Hamill, and Jacen Lanclos. 2021. "What Tasks to Automate? "An Investigation of What Tasks Make Sense to Automate for Future Aviation Platforms." Master's thesis, Naval Postgraduate School. http://hdl.handle.net/10945/68802

Department of the Army. n.d. "Future Vertical Lift (FVL) Family of Systems." Accessed November 2, 2021. https://asc.army.mil/web/portfolio-item/aviation_gray-eagleuas-2/.

———. 2019. *Army Modernization Strategy: Investing in the Future*. Washington, DC: Department of the Army. https://api.army.mil/e2/c/downloads/567887.pdf.

Ewart J. de Visser, Melanie LeGoullon, Amos Freedy, Elan Freedy, Gershon Weltman, and Raja Parasuraman. 2008. "Designing an Adaptive Automation System for Human Supervision of Unmanned Vehicles: A Bridge from Theory to Practice." In *Proceedings of the Human Factors and Ergonomics Society 52nd Annual Meeting*. 221–225. https://doi.org/10.1177/154193120805200405.

Ernst, Katie, Michael Wilson, David Durbin, Roth, Laura Militello, and Robert Copeland. 2020. “Human Factors in Future Vertical Lift, the U.S. Army’s Next Generation Rotorcraft.” In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 64 (1): 149–53. https://doi.org10.1177/1071181320641038

Foyle, David C., and Becky L. Hooey. 2007. *Human Performance Modeling in Aviation*. Boca Raton, FL, CRC Press. https://books.google.com/books?id=1ZoJAUGcXNcC

Gawron, Valerie Jane. 2019. *Workload Measures*. Boca Raton, FL: CRC Press. https://doi.org/10.1201/9780429019579.

Gertler, Jeremiah. Rep. 2021. *Army Future Vertical Lift (FVL) Program*. CRS Report No. IF11367. Washington, DC: Congressional Research Service. https://crsreports.congress.gov/product/pdf/IF/IF11367.

Guastello, Stephen J., Anton Shircel, Matthew Malon, and Paul Timm. 2015. “Individual Differences in the Experience of Cognitive Workload.” *Theoretical Issues in Ergonomics Science* 16 (1): 20–52. https://doi.org/10.1080/1463922X.2013.869371

Hart, S. G., and T.B. Sheridan. 1984. “Pilot Workload, Performance, and Aircraft Control 127 Automation.” AGARD Symposium on Human Factors Considerations in High Performance Aircraft, 18.1-18.12. https://www.researchgate.net/publication/23888817Pilotworkloadperformanceandaircraftcontrolautomation

Kantowitz, Barry H. 2000. “Attention and Mental Workload.” *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 44 (21): 3–456. https://doi.org/10.1177/154193120004402121.

Knisely, Benjamin M., Janell S. Joyner, and Monifa Vaughn-Cooke. 2021. “Cognitive Task Analysis and Workload Classification.” MethodsX 8 (January): 101235. https://doi.org/10.1016/j.mex.2021.101235.

Laughery, Ron. 1999. “Using Discrete-Event Simulation to Model Human Performance in Complex Systems.” In WSC’99. 1999 Winter Simulation Conference Proceedings. “Simulation - A Bridge to the Future” (Cat. No.99CH37038), 1:815–20 vol.1. https://doi.org/10.1109/WSC.1999.823275

Maclsaac, Margaret A. 1998 “The Effect of Automation on Helicopter Crew Communication: A Low-Fidelity Investigation.” Master’s Thesis, Embry-Riddle Aeronautical University. https://commons.erau.edu/db-theses/129

Militello, Laura G, Emilie Roth, Scott Scheff, Katie Ernst, Christen Sushereba, Julie Diiulio, and Devorah Klein. 2019a. “Toward an Optimally Crewed Future Vertical Lift Vehicle: Crewing Strategy and Recommendations.” U.S. Army Combat Capabilities Development Command.

Militello, Laura G, Emilie Roth, Scott Scheff, Katie Ernst, Christen Sushereba, Devorah Klein, and Scott Wonderly. 2019b. "Crew Configuration Analysis for Future Airborne Reconnaissance Operations." U.S. Army Combat Capabilities Development Command.

Moray, Neville. 1979. "Models and Measures of Mental Workload." Essay. In Mental Workload: Its Theory and Measurement: Proceedings of the NATO Symposium on Theory and Measurement of Mental Workload, Held at Mati, Greece, Aug. 30 - Sept. 6, 1977, 8:13–22. NATO Conference Series. New York, NY: Plenum P.

NASA. 2020. "NASA-STD-3001 Technical Brief" Accessed November 15, 2021 cognitive_workload_technical_brief_ochmo_06232020.pdf (nasa.gov)

Parasuraman, Raja, Toufik Bahri, John E. Deaton, Jeffrey G. Morrison, and Michael Barnes. 1992. "*Theory and Design of Adaptive Automation in Aviation Systems*." Washington, DC, Cognitive Science Lab. https://apps.dtic.mil/sti/citations/ADA254595.

Parasuraman, Raja, and Peter A Hancock. 2001. "Adaptive Control of Mental Workload." Essay. "Human Factors in Transportation." in *Stress, Workload, and Fatigue*, edited by Peter A. Hancock and Paula A. Desmond, 305–20. Mahwah, NJ: Lawrence Erlbaum Associates.

Pond, Travis, Brandon Webster, John Machuca, John Colombi, Michael Miller, and Randall Gibb. 2012. "Allocation of Communications to Reduce Mental Workload." *Procedia Computer Science* 8: 242–48. https://doi.org/10.1016/j.procs.2012.01.052.

Pop, Vlad and W. Stuart Michelson. 2018. "Human Workload Modeling for Autonomous Ground Vehicles." In *2018 NDIA Ground Vehicle Systems Engineering and Technology Symposium* 1–7. https://events.esd.org/wp-content/uploads/2018/07/Human-Workload-Modeling-for-Autonomous-Ground-Vehicles.pdf.

Powers, Dustin, and Andrew M. Gacy. 2018. "Using IMPRINT to Model Operator Staffing and Workload Considerations in a 24/7 Full-Service Mission Operations Center." In *2018 SpaceOps Conference* 1–12. https://doi.org/10.2514/6.2018-2394.

Rusnock, Christina F., and Brett J. Borghetti. 2016. "Workload Profiles: A Continuous Measure of Mental Workload." *International Journal of Industrial Ergonomics* 63 (January): 49–64. https://doi.org/10.1016/j.ergon.2016.09.003.

Salvi, Lucia. 2001. Development of Improved Performance Research Integration Tool (IMPRINT) Performance Degradation Factors for the Air Warrior Program. Report Number ARL-TR-2311. Army Research Lab, Aberdeen Proving Ground MD. https://apps.dtic.mil/sti/citations/ADA387840.

Sargent, Robert. 2021. “3-Day IMPRINT Training at NPS” Presentation Notes for the lecture, Monterey, CA

Secarea, V. V. J. 1990. “Beyond Knobs and Dials: Toward an Intentional Model of Man-Machine Interaction.” In *IEEE Conference on Aerospace and Electronics*, 763–769. https://ieeexplore-ieee-org.afit.idm.oclc.org/document/112864.

Shivers, Matthew. “Holistic Situational Awareness and Decision Making (HSA-DM).” Presentation for the Naval Postgraduate School Human Systems Integration Department, Monterey, California, November 2021.

Shivers, Matthew, and Rob Morony. 2021. “Human vs. Machine: Data for Situational Awareness, Decision Making and Robust Decisions.” DEVCOM Aviation & Missile Center. Accessed January 27, 2022, https://rt.cto.mil/wp-content/uploads/T9_HFE-TAG-Shivers_Morony-Data-for-Human-vs-Machine-consumption-PAOrelease.pdf

United States Army Aviation Center of Excellence. 2022. *UH-60 Series Aircrew Training Manua*l. Fort Rucker: USAACE.

Walliman, Nicholas. 2010. *Research Methods: The Basics : The Basics*. London: Taylor & Francis Group. ProQuest Ebook Central.

Wickens, Christopher D. 2002. “Multiple Resources and Performance Prediction.” Theoretical Issues in *135 Ergonomics Science*, 3(2), 159–177. https://doi.org/10.1080/14639220210123806

———. 2008. “Multiple Resources and Mental Workload.” *Human Factors: The Journal of the Human Factors and Ergonomics Society*. 50 (3): 449–55. https://doi.org/10.1518/001872008X288394

———. 2017. “Mental Workload: Assessment, Prediction and Consequences.” In *Human Mental Workload: Models and Applications,* edited by Luca Longo and M. Chiara Leva, 18–29. Communications in Computer and Information Science. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-61061-0_2.

Wickens, Christopher D., Robert S. Gutzwiller, and Amy Santamaria. 2015. “Discrete Task Switching in Overload: A Meta-Analyses and a Model.” International Journal of Human-Computer Studies 79 (July): 79–84. https://doi.org/10.1016/j.ijhcs.2015.01.002.

Wilson, Alexander. 2022. Interview by Abreu, Girton, Lord, Miller, and Zelada. March, 2022. Phone interview.

Wu, Changxu, Ling Rothrack, and Matthew Bolton. 2019. "Editorial Special Issue on Computational Human Performance Modeling." *IEEE Transactions on Human-Machine Systems* 49 (6): 470–73. https://doi.org/10.1109/THMS.2019.2942742.

Yahoodik, Sarah, Hesamoddin Tahami, James Underreact, Yusuke Yamani, Holly Handley, and Deborah Thompson. 2020. "Blink Rate as a Measure of Driver Workload during Simulated Driving." *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 64 (1): 1825–28. https://doi.org/10.1177/1071181320641439.

Young, Mark S., Neville A. Stanton, Guy H. Walker, Daniel P. Jenkins, and Paul M. Salmon. 2007. "Mental Workload in Command and Control Teams: Musings on the Outputs of EAST and WESTT." In Engineering Psychology and Cognitive Ergonomics, edited by Don Harris, 4562:455–64. Lecture Notes in Computer Science. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-73331-7_50.

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