**Autonomous ISR Analysis in Orbit: A Comparative Simulation of Human and AI Operators**

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## Dedication

This Praxis is dedicated to my son, Maximus. My precious boy, your boundless curiosity and passion for space rekindled the dreams I held as a child. It is because of you that I found the inspiration and courage to embark on this journey, exploring the vast possibilities of artificial intelligence. This work is a reflection of the wonder you bring into my life every day. May your passion continue to guide you to the stars.

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Lastly, heartfelt thanks to my partner, Chas, for managing the home front during countless long nights and weekends, and to my best friend, Leon, for providing the essential pep talks and emotional support that fueled my perseverance.

**Abstract of Praxis**

**Autonomous ISR Analysis in Orbit: A Comparative Simulation of Human and AI Operators**

Modern military space operations are increasingly complex and require rapid decision-making. However, current satellite intelligence, surveillance, and reconnaissance (ISR) operations rely heavily on ground support and human operators, making them slow and prone to delays, especially during high-intensity missions where time is critical. This Praxis explores the integration of artificial intelligence (AI) within satellite onboard architectures to address these limitations. The primary objective is to optimize military space operations by enabling swift, autonomous remote sensor data analysis and decision-making, without the need for continuous human intervention from ground stations.

Through AI system modeling, human cognitive modeling, and simulations comparing human operators to AI operator, this research examines the performance of AI-enabled ISR operations across various metrics, including accuracy, latency, and cognitive fatigue. The study tests three hypotheses: (1) AI-enabled ISR models can autonomously perform intelligence analysis and downlink intelligence data within 24 hours; (2) AI-enabled ISR models achieve significantly faster analysis durations than human analysts across mission cases; and (3) AI-enabled ISR models maintain more consistent accuracy than human analysts across all mission cases.

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## List of Abbreviations

| | |
|---|---|
| ACT-R | Adaptive Control of Thought-Rational |
| AI | Artificial Intelligence |
| AP | Average Precision |
| BI | Business Intelligence |
| C2 | Command and Control |
| CDAO | Chief Digital and Artificial Intelligence Officer |
| CFI | Cognitive Fatigue Index |
| CNN | Convolutional Neural Networks |
| CVA | Change Vector Analysis |
| DoD | Department of Defense |
| DRAM | Dynamic Random-Access Memory |
| DT | Decision-Making Time |
| ESA | European Space Agency |
| FPGA | Field-Programmable Gate Array |
| GAN | Generative Adversarial Networks |
| GB | Gigabyte |
| GEO | Geosynchronous Orbit |
| GEOINT | Geospatial Intelligence |

| | |
|---|---|
| IMPRINT | Improved Performance Research Integration Tool |
| IQR | Interquartile Range |
| ISL | Inter-Satellite Link |
| ISR | Intelligence, Surveillance, and Reconnaissance |
| kW | Kilowatt |
| LEO | Low-Earth Orbit |
| LiDAR | Light Detection and Ranging |
| LLM | Large Language Model |
| mAP | Mean Average Precision |
| MEO | Medium-Earth Orbit |
| MSWA | Micro Saint® Workload Analyzer |
| MTBF | Mean Time Between Failures |
| NLP | Natural Language Processing |
| NRO | National Reconnaissance Office |
| OD | Object Detection |
| PR | Precision-Recall |
| RAM | Random Access Memory |
| ROI | Regions of Interest |
| SAR | Synthetic Aperture Radar |

| | |
|---|---|
| SATCOM | Satellite Communication |
| SATSIM | Satellite Simulation |
| SDN | Software Defined Network |
| SD | Standard Deviation |
| SEU | Single-Event Upset |
| SRAM | Static Random-Access Memory |
| T | Mean Total Simulation Time |
| TLE | Two-Line Element |
| U.S. | United States |
| UHF | Ultra-High Frequency |
| VHF | Very High Frequency |
| YOLO | You Only Look Once |

## List of Equations

# Chapter 1—Introduction

## 1.1 Background

Intelligence, surveillance, and reconnaissance (ISR) operations in the U.S. military still run on outdated command and control (C2) systems. They rely heavily on human operators to interpret data and produce reports, which can slow the intelligence cycle down to days or even weeks before military leaders can take meaningful actions (Cooper, 2024; Menthe et al., 2021). Human factors such as fatigue, cognitive strain, and analytical mistakes further increase these delays (He et al., 2024; Laird et al., 2017; McCoy & Boys, 2013), which in turn undermine effective engineering management through mission setbacks (Zelik, 2021).

Total reliance on human operators adds another layer of risk to ISR operations. Mistakes and inefficiencies due to human limitations can create opportunities for adversaries to exploit, especially during high-intensity missions which rely on real-time intelligence data. These risks highlight the increasing need for AI-driven ISR systems that can deliver fast, reliable analysis and make autonomous decisions with minimal to no delays (Svatonova, 2016; Hoffman & Markman, 2001).

AI has the ability to reform satellite-based ISR operations by reducing workload pressure from human analysts which can ultimately increase overall mission effectiveness. AI can support autonomous decision-making, detect threats in near real time, and even apply predictive analytics (Maged et al., 2024) by quickly sifting through massive amounts of satellite imagery, which dramatically enhances the mission response speed (Cooper, 2024). Through integration of AI into ISR operations, the U.S. military can gain greater efficiency, precision, and adaptability in tackling today's national security challenges (Al Homssi et al., 2024; Maged et al., 2024; Govindan, 2022; Oche, Ewa, & Ibekwe, 2024).

In response to the growing need for AI implementation and wide adoption, U.S. Department of Defense (DoD) created Chief Digital and Artificial Intelligence Officer (CDAO) position through Directive 5105.89. This role guides the secure and ethical use of AI across military branches and defense operations. The directive also ensures that AI systems meet strict legal and ethical standards while the technology is used to protect national security interests (Department of Defense, 2024).

### 1.2 Research Motivation

It is important for the DoD to fast-track the safe and effective development of AI-enabled systems as global adversaries increasingly adopt AI for military purposes (Cooper, 2024; Maged et al., 2024; Cottam et al., 2019). DoD Directive 5105.89 addresses this urgency with secure and accelerated integration of AI across defense operations (Department of Defense, 2024). This initiative is especially important for improving satellite-based ISR functions, where current reliance on human operators to interpret remote sensing data can lead to delays, mistakes, and inefficiencies (McCoy & Boys, 2013; Laird et al., 2017; He et al., 2024; Al Homssi et al., 2024; Cottam et al., 2019).

### 1.3 Problem Statement

*Current United States military space-based ISR operations are slow, outdated, and dependent heavily on ground support, impeding rapid responses and risking high-intensity mission success.*

Legacy C2 systems create significantly large workload for human operators, making them solely responsible for carrying out sensitive tasks such as data analysis and decision-making—tasks that often lead to delays and inefficiencies when performed manually. Analyzing remote sensor data without automation increases the risk of error, influenced by factors such as fatigue, limited cognitive capacity, and variabilities in expertise among analysts (McCoy & Boys, 2013; Frieke et al., 2014). These nuanced gaps in the U.S. military's ISR operations are further exposed as the adversaries continue to make advancements in their AI-driven defense systems (Svatonova, 2016; Al Homssi et al., 2024).



### 1.4 Thesis Statement

*AI-enabled ISR models embedded onboard satellites are needed for optimizing military operations, enabling swift, autonomous data analysis and intelligence reporting necessary to increase mission success.*

Integrating AI into C2 systems can significantly reduce delays and inaccuracies in the intelligence reports by ISR analysts. AI can provide near real-time responses and streamline C2 processes, which can increase the efficiency and effectiveness of intelligence operations while reducing risks associated with human error and fatigue (McCoy & Boys, 2013; Al Homssi et al., 2024; Laird et al., 2017). Embedding autonomous systems within military satellites is critical for maintaining operational advantage over the adversaries, countering their efforts in outpacing U.S. in developing AI-driven defense systems (Govindan, 2022; Department of Defense, 2024).

### 1.5 Research Objectives

- *Build a cognitive model to represent human operator's remote sensing data analysis.*

- *Develop an AI performance model that demonstrates remote sensing data analysis.*
- *Create a target database and design mission scenarios for satellite simulation (SATSIM) environment.*
- *Execute identical test cases for both human and AI operator models to capture performance metrics such as accuracy, latency, and cognitive fatigue.*
- *Analyze and compare the simulation performance of human operator and AI operator, and determine which performs more effectively with respect to time and accuracy.*

### 1.6 Scope of Research

This Praxis uses a combination of simulations to compare the performance of a human cognitive model (representing a human operator) and an AI performance model (representing an AI operator) in analyzing remote sensor data. The AI performance model is developed based on existing object detection and natural language efficiency and accuracy benchmarks to simulate how an AI system would interpret satellite images. Conversely, the human cognitive model is built from the ground up to simulate how a human operator might conduct the same analysis. A SATSIM runs the mission scenarios, with the actions of the human operator and the AI's performance simulated separately, then integrated into the final simulation outcomes. A target database, derived from specific missions that had occurred in the past, is also embedded in the SATSIM to run through both operators. This method creates a controlled environment to assess and compare human and AI capabilities in ISR operations.

### 1.7 Research Assumptions and Limitations

This Praxis makes several assumptions and points out research limitations. According to the recent studies, it is safe to assume that embedding AI hardware within ISR satellites is feasible (Castillo et al., 2024). Hardware requirements for AI integration vary based on satellite type, mission objectives, and constellation configurations. This research assumes that existing hardware specifications documented in this research meet AI's diverse needs (Chintalapati et al., 2024; Al Homssi et al., 2022).

Some limitations exist in developing the human cognitive model, which simulates human operator analysis of remote sensing data. Accurately modeling human cognition and decision-making inherently involves subjective interpretation, as precise replication of human cognitive processes is not feasible and depends heavily on the chosen modeling methodology (Anderson, 2007; Gardin, 2010; Salvucci, 2016). This model assumes operators possess adequate expertise for effective analysis, but it is challenging to capture the subtleties and variability of human decision-making. Consequently, the accuracy and reliability of the model are dependent on the degree to which these cognitive approximations reflect realistic operator behavior (Frischkorn & Schubert, 2018).

## 1.8 Research Questions and Hypotheses

### 1.8.1 Research Question 1 and Hypothesis 1

*To what extent can AI-enabled ISR models embedded onboard satellites reduce the time required for intelligence analysis and data downlink?*

Null Hypothesis ($H_{01}$): AI-enabled ISR models cannot autonomously perform intelligence analysis and downlink intelligence data within 24 hours.

Alternative Hypothesis ($H_{11}$): AI-enabled ISR models can autonomously perform intelligence analysis and downlink intelligence data within 24 hours.

### 1.8.2 Research Question 2 and Hypothesis 2

*How does the analysis duration of AI-enabled ISR models compare to that of human analysts across mission scenarios?*

Null Hypothesis ($H_{02}$): There is no significant difference in analysis duration between AI-enabled ISR models and human analysts across mission scenarios.

Alternate Hypothesis ($H_{12}$): AI-enabled ISR models achieve significantly faster analysis durations than human analysts across mission cases.

### 1.8.3 Research Question 3 and Hypothesis 3

*How does the accuracy of AI-enabled ISR models vary relative to human analysts across different ISR mission complexities?*

Null Hypothesis ($H_{03}$): There is no significant difference in accuracy between AI-enabled ISR models and human analysts across mission complexities.

Alternate Hypothesis ($H_{13}$): AI-enabled ISR models maintain more consistent accuracy than human analysts across all mission cases.



## 1.9 Organization of Praxis

This Praxis is organized into five chapters, each covering a different aspect of the research process. Chapter 1 serves as the introduction, outlining the research problem, objectives, significance of the study, and the research questions. It establishes the need for AI-enabled systems in satellite-based ISR operations and provides an overview of the challenges currently faced in military remote sensing, particularly those related to human-in-the-loop decision-making.

Chapter 2 presents a comprehensive literature review. It covers the foundations of satellite communication architectures, image processing techniques, and the role of AI in ISR operations. This chapter also explores human cognitive models in remote sensing, setting the groundwork for simulating a human operator in later sections. In addition, it reviews tools and techniques for simulating satellite operations and identifies gaps in the existing literature that this study aims to address.

Chapter 3 explains the methodologies used to complete this Praxis. It elaborates on the design and implementation of both the human cognitive model and the AI operator performance model, as well as the SATSIM environment used to test and compare their performance. It documents the data collection procedures, mission cases, and lists the performance metrics used to evaluate both operators.

Chapter 4 discusses the results of each simulation separately, and then places those results within the operational context by merging AI operator and human operator data with the SATSIM outputs for each mission case. It then evaluates each mission outcome based on the 3 hypotheses, and concludes with sensitivity analysis.

Finally, Chapter 5 closes the Praxis with a summary of key findings and explores their relevance in modernizing military ISR operations. This chapter lists the future research opportunities to build on these results, and reflects on how this work contributes to the field of AI integration and satellite-based ISR.