

Predicting and Protecting the Cognitive Health of Operators in Isolated, Confined, and Extreme Environments

Doctoral Consortium

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ABSTRACT

Operators’ cognitive performance is often critical for success and safety in isolated, confined, and extreme (ICE) environments such as spaceflight and wilderness medicine. Future autonomous systems may leverage predictions of cognitive states to improve human-system performance. Current approaches of estimating cognitive states, such as surveys or behavioral measures, are obtrusive, task-specific, or cannot be used in real-time. Physiological modeling, where biosignals are used to predict operator cognitive states, has the potential to overcome these limitations. My research develops predictive models of cognitive states and investigates cognitive health in ICE environments, aiming to inform adaptive autonomous systems and mitigate health and performance decrement.

KEYWORDS

Predictive Modeling; Human-Agent Teaming; Cognitive State; ICE

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1 INTRODUCTION

Operational environments often require humans to team with multiple agents, including other humans and autonomous systems. These settings, such as spaceflight, aviation, medicine, and military operations, are characterized by trained users, ambiguity, hazards, and degraded performance and safety resulting from improper action. In future operational environments, the ability to predict operators’ cognitive states could inform adaptive autonomous systems and improve safety and performance [13].

Some operational crews work in isolated, confined, and extreme (ICE) environments, such as space, polar, or deep sea settings. These crews face isolation from their typical social network, confinement, and extreme, dangerous conditions [7]. Isolation is also associated with decreased cognitive functioning [1, 3, 6]. To best support crews operating in ICE environments, it is important to understand factors of these environments that affect crewmembers’ cognitive

health (the ability to clearly think, learn, and remember [12]) and to develop means of modeling the cognitive states of crewmembers subject to the unique challenges of ICE settings.

Current methods of measuring cognitive states are insufficient for operational environments. Though subjective questionnaires are widely-accepted, their use requires interrupting an operator’s task. Behavioral and task-based measures are often specific to given tasks and lose validity with changes to tasks or protocols. Physiological measures, however, do not require interrupting an operator’s work and do not rely on task-specific elements. As a result, models based on physiological measures may show robustness to changes in tasks or protocol, as well as utility across different tasks.

To better support crews in multi-agent, operational, ICE environments, we aim to 1) develop physiological models of cognitive states practical for operational use, 2) assess the transferability of physiological models across tasks, and 3) investigate factors influencing cognitive health in ICE environments.

2 PREDICTIVE MODELING OF COGNITIVE STATES USING PHYSIOLOGICAL DATA

In future complex operational environments, the ability to predict an operator’s trust, mental workload, and situation awareness (TWSA) can facilitate improved safety and performance [5, 10, 11, 13]. Predictive models of TWSA must work in near real-time if they are to be useful in real-world operations. These models would provide additional operational utility if they are accurate across different users. Collecting demographic information on operators may be impractical in time-constrained situations [15, 16]. Furthermore, necessitating collection of demographic data may decrease a tool’s acceptability, especially where an operator’s performance affects their career; [2, 4]. Real-time, operator-agnostic models of TWSA are of critical interest as we look to improve the performance of human-agent teams in complex operational environments.

We explored the implications of excluding operator-specific information and features that cannot be used in real time on modeling TWSA in the same experiment [14]. We built regression models of operator TWSA from electrocardiogram, respiration, electrodermal activity, and eye-tracking data in a supervisory task where participants (n=10) worked alongside an autonomous system on a simulated deep space habitat. We performed feature shrinkage to reduce our feature set and stability selection to reduce variability in feature selection. Additionally, we used simulated random data to demonstrate our pipeline’s robustness to false positives from high-dimensional data. Finally, we used internal cross-validation to assess the predictive accuracy of our models on unseen trials and on unseen people. This was done with different subsets of



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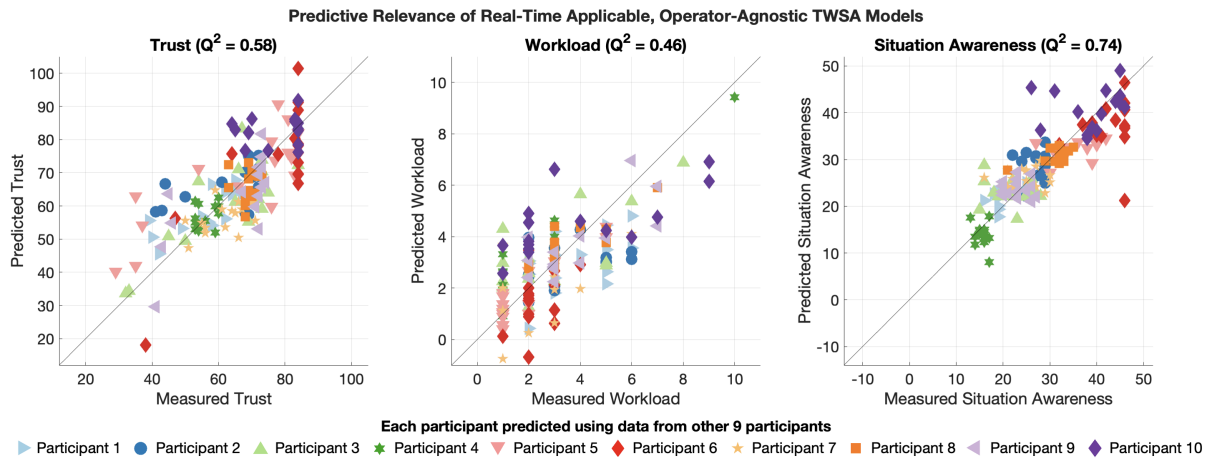


Figure 1: Leave-One-Participant-Out cross validation predictive performance for real-time applicable, operator-agnostic models of trust (left), workload (center), and situation awareness (right).

available features to assess the utility of real-time usable models and of operator-agnostic models. The feature selection was not included in the cross-validation; comprehensive cross-validation is future work. Leave-one-participant-out cross validation predictive performance for each of TWSA is shown in Figure 1. We improve on prior work that relies on proxy measures by using validated questionnaires as the target variables in predicting TWSA. We also improve on work modeling singular cognitive states by predicting each of TWSA independently in one integrated task. Finally, our modeling approach improves upon classification techniques by modeling TWSA as continuous constructs. We showed that model performance decreases with less information available, but that real-time applicable, operator-agnostic models still demonstrate viability for use in predicting operator TWSA [14].

3 ASSESSING THE TRANSFERABILITY OF PHYSIOLOGICAL MODELS ACROSS TASKS

Physiological models do not directly rely on task-specific elements (such as response time or accuracy) and thus may be robust to changes in tasks or usable across tasks. In this work we develop models of TWSA from electrocardiogram, respiration, and eye tracking data recorded as operators perform different spaceflight-relevant tasks. We assess the ability of the models to transfer to both new participants and to new tasks.

In a simulated space habitat maintenance task, participants ($n=15$) worked with an autonomous system to maintain an air revitalization system (ARS) [9]. The autonomous system controlled the ARS while participants acted in a supervisory role. In a separate simulated spacecraft piloting task, participants ($n=15$) tracked a space station with a docking camera, performed verbal callouts, monitored a secondary task light, and worked with an autonomous system to complete a decision task [8]. Both tasks elicited changes in participants’ TWSA. Physiological signals were recorded from participants during trials and participants rated their TWSA via subjective questionnaires after each trial. Regression models of TWSA were fit with an emphasis on model stability and generalizability.

The datasets were split into training and testing sets to enable evaluation of the models’ predictive accuracy on new participants. Next, models built with data from the habitat maintenance task will be used to predict the TWSA of participants performing the piloting task, and vice versa. The habitat maintenance and piloting tasks emulate responsibilities of future deep space habitat operators, but vary the level of control assigned to the operator. Our use of consistent physiological sensors, subjective questionnaires, and sample pool enables a focus on the task’s influence on model accuracy. Results will both provide insights into the utility of physiological models of cognitive states across tasks and identify physiological measures that are robust to inter-individual and task differences.

4 INVESTIGATING COGNITIVE HEALTH IN ICE ENVIRONMENTS

Next, I will study cognitive health in ICE environments with an emphasis on complex, extended-duration teaming scenarios. I will use qualitative interviews to learn how skilled operators (such as astronauts, emergency medicine doctors, and military leaders) process information in ICE settings. Building on my current research on modeling cognitive states, I will use the themes identified in the interviews to design lab-based experiments investigating neurophysiological measures of cognitive health via electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS). I will leverage a space habitat mockup at CU Boulder - an ideal environment for isolating up to four individuals and controlling the information they have access to. Finally, I will conduct field studies at Mars Desert Research Station, an analog Martian habitat, evaluating the transfer of modeling capabilities from the lab to field settings using wearable sensors. This extended-duration study in an ICE environment provides an ideal culmination for this research and paves the way for its use in real-world applications.

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