# Wearable Brain and Body Sensing for Multimodal Assessment of Cognitive Workload and Training

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## *ABSTRACT*

*The efficiency and safety of complex high precision human-machine systems such as in aerospace and robotic surgery are closely related to the cognitive readiness, ability to manage workload, and situational awareness of their operators. Accurate assessment of mental workload could help in preventing operator error and allow for pertinent intervention by predicting performance decline that can arise from either work overload or understimulation. Neuroergonomic approaches based on measures of human body and brain activity collectively can provide sensitive and reliable assessment of human mental workload in complex training and work environments. This paper outlines the potential of wearable brain and body imaging methods for the assessment of mental workload via neuro/physiological signals, and provides a study design for comparative evaluation of workload during multi-domain cognitive tasks with simultaneous multi-modal biosensors. Such comprehensive neuroergonomic assessment utilizing both neuroimaging and physiological monitoring can inform development of next generation neuroadaptive interfaces and training approaches for more efficient human-machine interaction and operator skill acquisition.*

**Keywords**: Cognitive Workload, fNIRS, EEG, Eye-tracking, Neuroergonomics, Mobile Brain/Body Imaging

## 1.0 INTRODUCTION

Human performance on any type of goal or task is related to the amount of cognitive workload that is required to be proficient at completing it. Each person will have their own unique cognitive profile, and be more mentally efficient at performing certain types of tasks [1]. Through targeted training, operators can improve their abilities and become more efficient at their work in a shorter period of time.

Mental workload plays a critical role in many complex command and control systems. The efficiency and safety of complex high precision human-machine systems such as in aerospace and robotic surgery are closely related to the cognitive readiness, ability to manage workload, and situational awareness of their operators. Subjective operator reports, physiological, and behavioral measures are not sufficiently reliable to monitor cognitive overload that can lead to adverse outcomes. A key feature of the concept of mental workload – that reflects how hard the brain is working to meet task demands – is that it can be dissociated from behavioral performance data. Experienced human operators can maintain performance at required levels for an extended period through increased effort and motivation or strategy changes, even in the face of increased task challenge. Sustained task demands, however, eventually lead to performance decline unless the upward trend in mental workload can be used to predict subsequent performance breakdown. Consequently, it is important to assess mental workload independent of performance measures during training and operational missions. Neuroergonomic approaches based on measures of human body and brain activity can provide sensitive and reliable assessment of human mental workload in complex training and work environments [2].

It is particularly important to assess and measure operator cognitive workload in the context of military operations, where performance failures could result in catastrophic losses. Accurate assessment of mental workload could help in preventing operator error and allow for pertinent intervention by predicting performance decline that can arise from either work overload or understimulation.

Furthermore, a neurophysiology-based measure of expertise must be defined in relationship to behavioral performance. However, at any given level of performance, a neuronal measure of expertise that monitors the attentional and control resources that the individual must utilize to maintain that level of performance could be expected to vary widely between relatively lesser and greater expertise. That is, even at 98-100% performance levels, where performance measures cannot differentiate between trainee capacities, some individuals will be performing at close to their peak performance because their mental workload is close to the limit of their capacity, whereas others will be well below their workload capacity. An assessment of the cortical activity necessary to perform at a given level would indicate the cognitive resources available for more situational demands, consistent with greater expertise.

Hence, neuroscience-informed training methods are expected to allow for officers to advance through skill modules at a faster rate, saving both time and budget. To that end, we will go through the different modalities of biosensor measurements, outline our recent studies, and present a new study design that will allow us to determine what is the best way to measure the effects of training using cognitive workload assessments, as well as what are the most effective training tasks to improve a confluence of mental skill domains simultaneously.

The study design presented here is based on a training protocol utilizing six distinct cognitive tasks that are relevant to a user monitoring flight or unmanned aerial vehicle (UAV) field operations: *Situation awareness*, via monitoring multiple planes in an air traffic controller style simulation; *Vigilance*, using the continuous performance task to sustain attention on visual stimuli over a sustained period; *Working memory*, using a radar indicating the spatial locations of multiple aircraft; *Inhibitory* control, making split-second decisions on whether visual callsigns are friend or foe; *Shifting attention*, using the trail making task to train multitasking; And *risk assessment*, to maximize gains in low-risk low-reward versus high-risk high-reward situations. Each task is trained on for three sessions over a one-month period, and has both low- and high-workload conditions.

To measure the induced cognitive workload of each task, and thus to understand the mental effort of the operator in different cognitive areas, we employ a comprehensive neuro and physiological sensor suite that aligned with the neuroergonomic approach [2, 3]. For neuroimaging, we used functional near infrared spectroscopy (fNIRS) and electroencephalogram (EEG), and for physiological signal monitoring we used electrocardiogram (ECG), plethysmography (PPG), electrooculogram (EOG), and remote eye tracking. Each of these modalities is known to be sensitive to changes in cognitive workload in their own ways; the study's goal is to combine them to determine the best combination of factors to most accurately assess workload while on task. With a deeper ability to do this, we can better determine the effectiveness of training and speed of learning so as not to waste unnecessary resources.

These also allow us to computationally determine domains of cognition that overlap between the six tasks. For example, reaction speed, memory, and visual acuity are relevant parameters to many of the tasks. Training can be made more efficient by designing a protocol that enhances these skills in the fewest number of tasks and the fastest time.

This comprehensive workload assessment utilizing both neuroimaging and physiological monitoring can inform developing next generation neuro-adaptive training approaches for more efficient skill acquisition.

# 2.0 COGNITIVE WORKLOAD AND APPLICATIONS

## 2.1 Working Definition

Cognitive workload is a description of the collective external multidimensional demands necessary for an individual to complete a task in proportion with their internal skill level [4, 5]. To simplify, any action, whether physical, mental, or a combination, will take some amount of mental effort to complete. This may range from the subconscious and trivial action of picking up a cup to the intense focus necessary to coordinate a constant stream of planes as an air traffic controller. These external factors place different levels of physical, mental, temporal, and frustration demands on the individual, to name a few. In order to compensate for these demands and successfully achieve the desired outcome of task performance, a requisite level of skill must be acquired through experience and learning. But because humans are not computers, we are able to complete tasks successfully at a variety of skill levels by changing the amount of effort we input. A low skilled individual can achieve success with high effort just the same as a high skilled individual can achieve it with lower effort. It is this amount of effort required that we call cognitive workload.

## 2.2 Cognitive Load Theory

Cognitive load theory describes how mental workload is related to performance and learning. Because workload is a product of the inherent biological limits of the brain, it can be equated as the sum content of thoughts held concurrently in working memory during task performance [6, 7]. Human working memory is limited in the case of new or vital information to around seven “chunks” on average, plus or minus two [8, 9]. This chunking is a vital part of learning, and each chunk can be categorized into one of three types [10, 11]. There is intrinsic load, which is necessary for the completion of the task and inherent to the required actions; extraneous load, which includes distractors and unnecessary workload; and germane load, which is inherent to learning and skill acquisition [12]. The two former categories, intrinsic and extraneous, can also be classified as “mental load”, whereas germane load is classified as “mental effort”, emphasizing that to learn or improve a skill, voluntary effort is required [13].

## 2.3 Workload Performance Curve

The interaction between the current level of mental workload and performance on a task can be described by the inverted U-shaped curve known as the Yerkes-Dodson curve [14]. Their experiment, as well as many after, determined that the best performance occurs when workload is neither too high nor too low. When the difficulty of the task or presence of distractors is too high and causes high levels of workload, performance drops as a person becomes frustrated or is unable to meet demands. Conversely, when the task is too easy or the operator too skilled, the very low levels of workload required allow mind wandering and a lack of focus, which also causes performance to drop. When the induced workload is at the peak of the inverted U-shaped curve, the highest levels of germane load, and therefore learning, occur [15, 16]. Training can be designed around this concept in order to optimize the efficient acquisition of skill.

## 2.4 Methods of Measurement

Because cognitive workload is distributed throughout the brain and is an interaction of external and internal factors, there are multiple methods used to measure workload. The simplest is to measure behavioral performance and grade it on level of success [17]. Although this directly correlates to the output of skill, it is unable to accurately define internal states. The next method is by using subjective surveys such as the NASA-TLX [18]. This asks individuals to grade their own levels of workload, but is inherently lacking due to asking people to objectively score themselves, which is difficult, and may be marred by memory because it is always given post-task performance. A third method is to use secondary-task performance, which inserts an unrelated task to the primary goal to measure the reserve cognitive capacity [19]. The concept is that any mental resources not necessary to be proficient in the main goal will be used by the secondary one, giving a measure of percentage total mental capacity, but the obvious downside is that this is both distracting and puts a lot of strain on the performer. The final method is to use physiological and neural imaging to achieve an objective measure of the inner workings of the mind, without putting undo strain on the performer, distracting them, or using unreliable subjective measures. These will be discussed in detail in Section 3.

## 2.5 Representative Drexel Collaborative Studies

### 2.5.1 Air Traffic Control Simulations

Air Traffic Control (ATC) operators are required to have high situational awareness, intense focus, and strong working memory to safely direct the flight path of multiple airplanes in transit. In collaboration with US Federal Aviation Administration William Hughes Technical Center over the last decade, we have conducted a series of studies where we utilized mobile and wearable neuroimaging with typical and emerging ATC scenarios [20-25]. In one of the first studies where we used fNIRS neuroimaging out of lab, the primary objective was to use neurophysiological measures to assess cognitive workload and usability of new interfaces developed for complex ATC systems. To test their skills and the workload induced by different types of ATC information display, an fNIRS system over the prefrontal cortex was used during a series of tasks [26, 27]. To modulate the amount of induced workload, either 6, 12, or 18 aircraft were presented for monitoring, and it was found that fNIRS was sensitive enough to distinguish between the different levels. In addition, the information in the task was presented in one of two ways: by voice communications or electronic data communications. It was found that the voice comms induced a significantly higher level of mental workload. The results overall indicated that brain activation as measured by fNIRS provides a measure of mental workload in this realistic air traffic control task [23]. In practice, this demonstrated the potential of the approach to be translated for practical use for potential assessment of future ATC developments in communications and plane monitoring. Finally, taking it a step further, more futuristic applications are to apply this for each individual operator in real-time to personalize their workflow during operation so that they are best able to perform their duties.

### 2.5.2 Piloting Aerial Vehicles

Many skills that are relevant to ATC operators are also shared by pilots controlling aircrafts, and both professions must have a deep understanding of one another in order to work together effectively. In a series of studies, we investigated the potential of wearable neurotechnology for cognitive workload and training assessment and intervention for aircraft piloting tasks with a range from low-fidelity simulators, to high-fidelity moving platform simulators, and even during actual flight in real aircraft [23, 24, 28-35].

In one of the earlier studies we investigated the impact of training, with novice participants practicing UAV piloting tasks over a 9 day period [23, 36]. The two types of flying tasks used were a turn-to-approach the runway, where the UAV had to be maneuvered through a series of rings in the air to simulate a final approach, and a landing task, where the actual touchdown occurred. In addition to flight performance, self-reporting surveys were taken with the NASA-TLX, and fNIRS was measured from anterior prefrontal cortex (PFC). Over the span of nine days of training, as expected, it was found that performance improved and self-reported measures indicated a decrease in perceived workload as expertise was acquired. Moreover, localized PFC cortical activity as measured with fNIRS decreased, also indicating a decrease in workload to match the increase in skill. In fact, the fNIRS measures displayed a pattern matching a standard learning curve, where workload increased slightly as participants accommodated to the task, before dropping significantly when a new level of skill was reached [37]. This concurs with our other studies [38] and shows the potential of an objective assessment of skill acquisition confirmed with other studies via longitudinal monitoring of localized neurophysiology with fNIRS. One futuristic application could be to use neuroimaging to proactively adapt the training [35] or optimize neurostimulation [32] and overall can provide additional detailed information about participants readiness and level of training.

#### 2.5.3 Multimodal Physiological and Neuroimaging

A single neuroimaging measure could provide useful information on the mental state and inner workings of the brain at work, and as different modalities have different advantages and disadvantages, multiple imaging modalities combined is expected to deliver even more detailed information by utilizing the best aspects of each. And, hence, understanding the complementary and shared information in biosignals such as fNIRS, EEG, ECG and other physiological modalities is a long-standing interest[39]. In a series of multimodal studies, we tested that and incorporated multiple measures to potentially improve accuracy/performance of brain computer interfaces [40-43]. In one recent study, we used a classical verbal N-back task with fNIRS, EEG, and cardiovascular measures together [40]. Using a pseudorandom presentation of 0-back, 2-back, and 3-back letter presentation tasks, linear discriminant analysis was used to classify workload for each combination of fNIRS, EEG, and physiological signals to determine the best grouping for workload assessment. Here, it was found that while all three modalities have the ability to classify workload levels, the fNIRS+EEG combination provided the best results, but the addition of heart rate and respiratory measures did not significantly improve classification. While this proves the strength of multimodal imaging, it does not dismiss the concept of incorporating body measures, as only a single domain of cognition was tested, and in the experiment described in this paper additional modalities including eye tracking are used.

## 3.0 WEARABLE BODY AND NEUROIMAGING

### 3.1 Neuro-Physiological Measures

The brain and body hold a wealth of externally measurable information about the mental states and internal workings of the mind. Multiple different biosensors can be used simultaneously to collect this complementary information to obtain a more complete and deep understanding of operator workload during tasks. In our experiment, a suite of six unique sensors was utilized to measure correlates of cognitive workload from each participant.

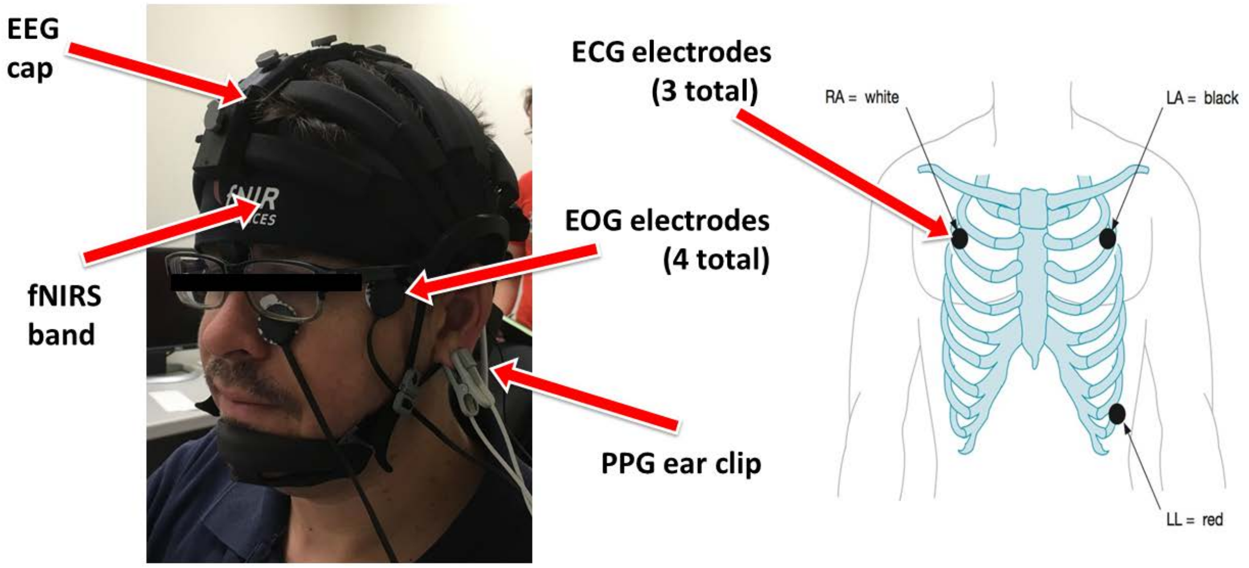


**Figure 3-1: Sensor suite displaying fNIRS, EEG, ECG, PPG, and EOG (eye tracking not shown here).**

### 3.1.1 Functional Near-Infrared Spectroscopy

Functional near-infrared spectroscopy uses light in the wavelengths of around near-infrared range (optical window of human tissue is 700nm to 900nm range just around red color) to measure changes in the local concentration levels of oxygenated- and deoxygenated-hemoglobin in the cortical tissue. These values are hemodynamic response and relate with the specific neuronal activity of the measured brain areas via a well-known concept of neurovascular coupling, and hence provide brain activity changes information on the relative changes of oxygenated blood concentration[44]. Furthermore, fNIRS systems can be built miniaturized and are suitable for out-of-lab and even ambulatory measurements[45-51]. In our experiment, the fNIR Devices Model 1200 was used to record prefrontal cortical hemodynamics [36]. It recorded from 16 optode locations at a rate of 2 Hz. Raw light intensity taken at 730 and 850 nm was filtered with a low pass FIR filter and a sliding window motion artifact rejection (SMAR) algorithm [52] in Matlab, and then processed using the modified Beer-Lambert Law into oxygenated and deoxygenated hemoglobin values.

### 3.1.2 Electroencephalogram

EEG measures highly temporally localized electrical activity of neuron groups in the cortex via electrodes, conductive metals, placed over the scalp. Its strength is in determining the precise timing of brain reactions to stimuli and thoughts, as well as provide higher order measures of brain waves in the alpha, beta, delta, and theta frequency bands of activity [53]. EEG systems have been undergoing decades of development, and currently many types of systems such as active vs. passive and dry vs. wet electrodes as well as battery-operated and high density shielded stationary systems exist[54, 55]. There has been many developments on EEG methodology towards enabling mobile brain imaging in more naturalistic settings[56-58]. In our experiment, the Cognionics HD-72 dry electrode EEG was used to record full head neuronal excitement measures. Data was collected from 32 electrodes at 500 Hz after checking for impedance and processed using a notch filter at 60 Hz, followed by a bandpass filter between 1-59Hz. Each channel was evaluated for quality using Automatic Subspace Reconstruction (ASR) [59] with default settings implemented in EEGLAB [60]. Continuous band power calculations for each channel were done using Welch's power spectral density of the EEG signal with a moving window of 2 s. Power spectra were divided into delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (>30 Hz) bands for workload assessment.

### 3.1.3 Electrocardiogram

Heart activity is affected by mental effort and environmental stressors [61]. This includes not just heart rate and heart rate variability, but the shape of the signal and other temporal measures. In this experiment, heart activity was recorded from three electrodes via an extension to the Cognionics headset. Heart rate variability and other workload measures were processed using Matlab [62].

### 3.1.4 Plethysmography

Plethysmography (PPG) is a versatile modality for measuring blood flow, and can be used to supplement ECG and add additional factors to heart monitoring. Here, systemic blood flow was recorded from an optical ear clip extension to the Cognionics headset. PPG assists in measuring heart rate variability and blood flow workload measures [61].

### 3.1.5 Electrooculogram

Blinks, saccades, and eye movements correlate with mental workload [63]. Using a distinct EOG system separate from EEG electrodes allows for cleaner signal that is not contaminated by other information. In the experiment, eye movements were recorded from four electrodes via an extension to the Cognionics headset, two placed above and below the left eye, and two played on the outside of both eyes.

### 3.1.6 Eye Tracking

Saccade velocity, fixations, pupil diameter, and their variations are correlates of cognitive workload [64]. Eye tracking can also provide a more accurate assessment of precise gaze location, whereas EOG may be able to measure smaller, subtler movements of the eye. In this experiment, the Smart Eye Aurora recorded eye gaze and pupil diameter at 60 Hz and was processed using OGAMA software.

# 4.0 PROTOCOL

The methods used in this sample study presented here focus on highly detailed recording for a single session of a single task. The purpose is to determine the limits of cognitive workload classification in a short time on a naïve operator.

## 4.1 Participants

Twenty-three participants between the ages of 18 to 48 (7 males, mean age 23 years) volunteered for the study. All subjects confirmed via survey given in person that they met the eligibility requirements of being right-handed with vision correctable to 20/20, did not have a history of brain injury or psychological disorder, were not on medication affecting brain activity, and were United States citizens or permanent residents. Prior to the study all participants signed consent forms approved by the Institutional Review Board of Drexel University.

## 4.2 Experimental Setup

The sample experiment was performed over one session (the first session among longitudinal repetitions) lasting up to one hour. Participants were seated upright in front of a computer with a standard mouse and keyboard one meter away from the monitor. They were fitted with an fNIR Devices Model 1200 headband over the forehead, a Cognionics HD-72 dry electrode cap, and a Cognionics extension providing sticky electrodes for the ECG (3 electrodes), EOG (4 electrodes), and PPG ear clip. Eye tracking was calibrated using the Smart Eye Aurora system recording gaze location and pupil diameter. The task described below was coded using the Python extension PsychoPy. The task was preceded by instructions and practice trials for each difficulty condition where participants could familiarize themselves with the procedure and ask clarifying questions. The task was designed to take 5-8 minutes to complete, and each of the two difficulties was performed three times in random order.

### 4.3 Inhibitory Control Task

The task tested here was designed to represent simplified operations often required by UAV monitors based on previous lab experiments in the literature. The identification of other objects in flight as friendly, neutral, or hostile may sometimes take until the last second to happen, or may even be misidentified at first before correction. Therefore, quick reaction times to interact with these other objects or even change a reaction increases safety in the air. In this vein, an adaptation of the go-stop paradigm was used to test participants' ability to stop a reaction to a stimulus [65, 66]. Participants were instructed to react to a "start" stimulus flashing on screen for 150 ms and attempt to press a button. In the low workload condition, the start stimulus either remained the same or changed to an "ignore" stimulus for 350 seconds, which participants were told to treat identically to the previous target. In the high workload condition, the start stimulus either remained the same or changed to a "stop" stimulus, which participants were told to attempt to stop their button press before it completed.

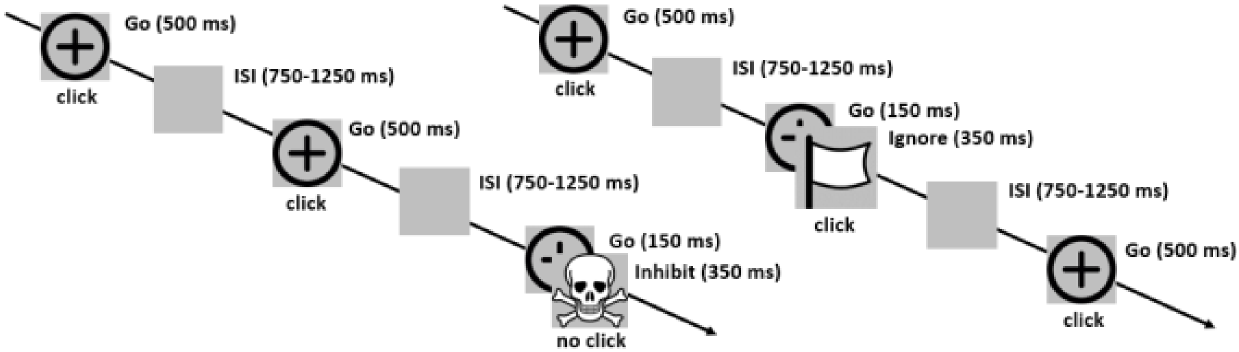


**Figure 4-1: Cross (go) stimuli is always shown for 150 ms, followed by 350 ms of cross, flag (go), or skull (stop).**

## 5.0 RESULTS

Preliminary results from the study are presented below for each modality separately. These focus on a single session per subject for the inhibitory control task.

### 5.1 Behavioral Performance

Participants were scored according to their percentage accuracy overall in correct responses for each condition, as well as their reaction time to each stimulus. A significant difference was found in both measures, with higher accuracy in the easy condition ($F_{1,109} = 189.6$, $p < 0.001$) and lower reaction times in the easy condition ($F_{1,109} = 56.3$, $p < 0.001$), both indicating better performance.

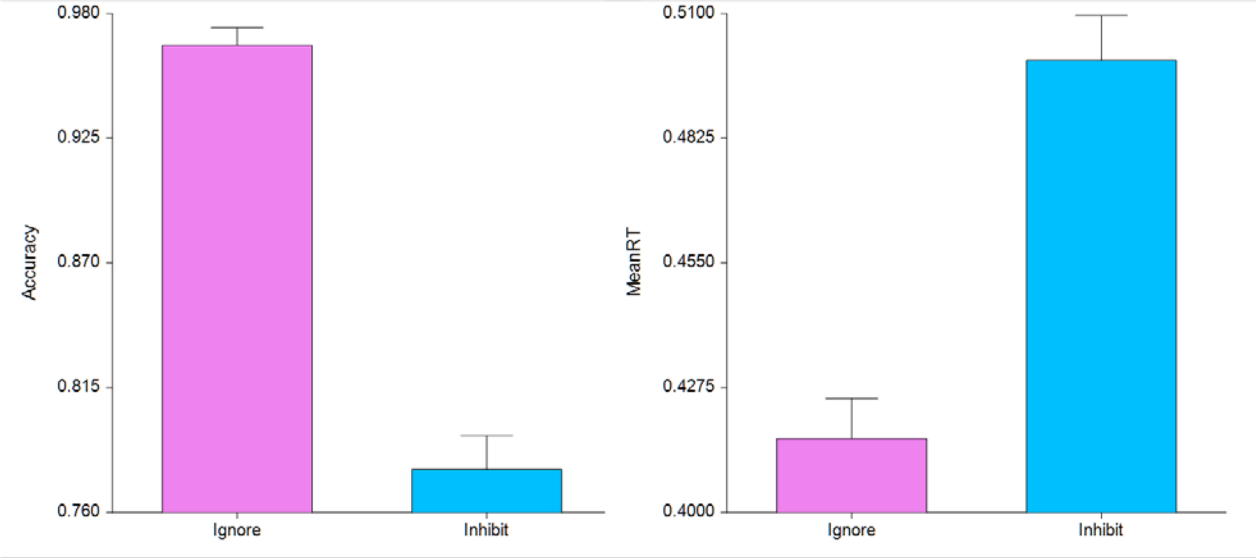


**Figure 5-1: Accuracy percentage and mean reaction times for each condition (bars are SEM).**

## 5.2 Eye Tracking Metrics

A variety of eye tracking measures were taken spanning pupil diameter, saccade velocity and distance, and number and length of fixations. A significant difference between conditions was found in the average saccade length ($F_{1,71.5} = 5.4$, $p < 0.05$), with lower saccade lengths indicating higher workload.

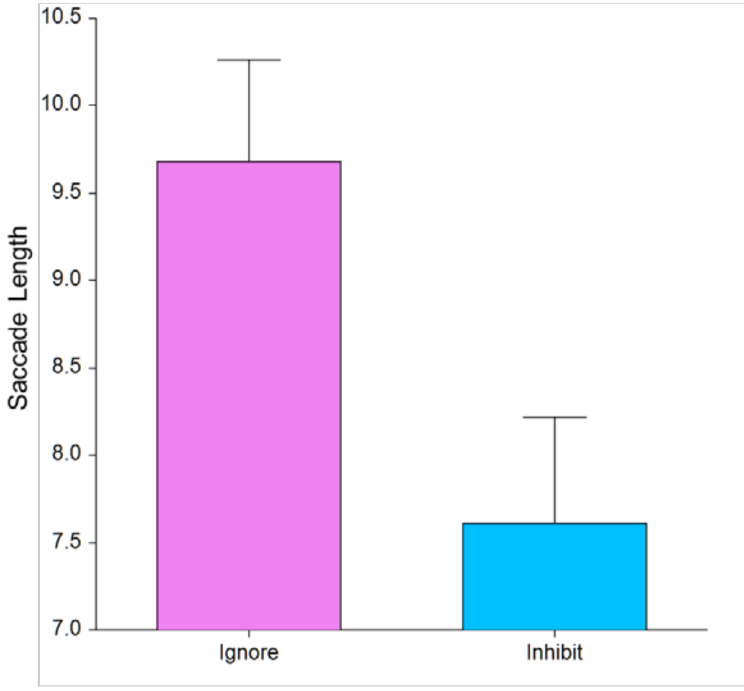


**Figure 5-2: Average saccade length for each condition (bars are SEM).**

## 5.3 Functional Near-Infrared Spectroscopy Measures

Relative oxygenated hemoglobin concentrations in the prefrontal cortex were compared between conditions. Subjects with lower than 60% accuracy were excluded due to not performing the task properly. In optode 1 found in the left dorsolateral prefrontal cortex, a significant difference between conditions was found for oxygenated hemoglobin ($F_{1,81.6} = 6.04$, $p < 0.05$).

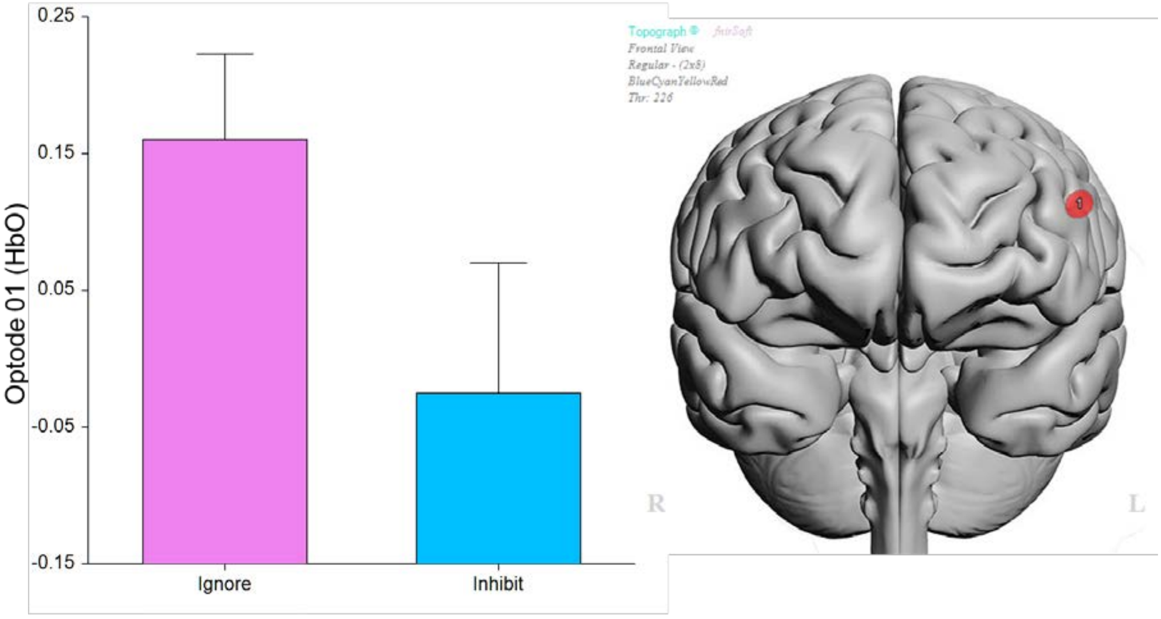


**Figure 5-3: fNIRS oxygenated hemoglobin in optode 1 (left dorsolateral prefrontal) and anatomical representation.**

## 5.4 EEG Measures

Normalized alpha power was calculated to measure workload correlates. Subjects with lower than 60% accuracy were excluded due to not performing the task properly. Several electrodes were found to have significant differences between the easy and hard conditions, including AFF2 ($F_{1,85.9} = 6.26$, $p < 0.05$), AFF4 ($F_{1,85.9} = 4.63$, $p < 0.05$), and FFC6h ($F_{1,90.5} = 4.32$, $p < 0.05$).

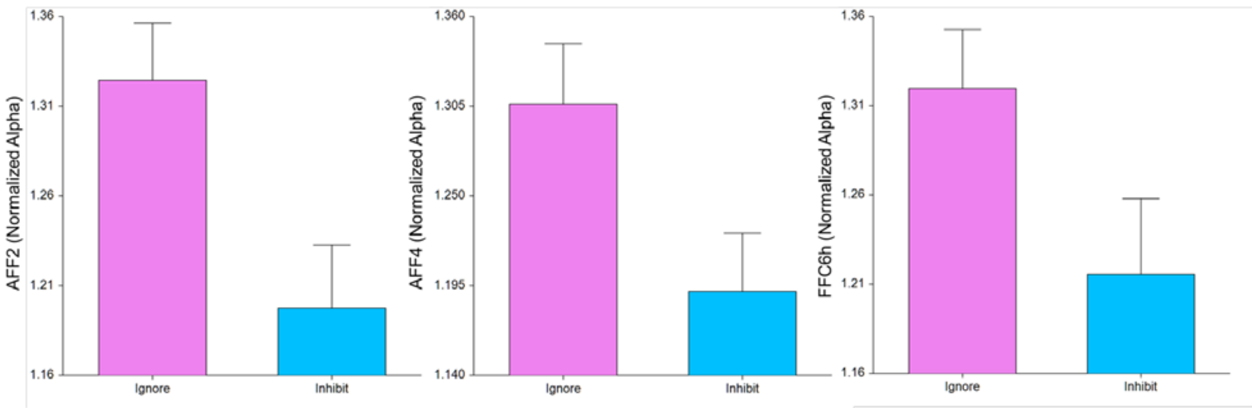


**Figure 5-4: EEG Normalized alpha power for AFF2, AFF4, and FFC6h.**

# 6.0 DISCUSSION

This paper highlighted the potential of combined use of neuro/physiological measures for the assessment of cognitive workload and training with real-world contexts in mind. There's a growing literature of evidence from diverse labs around the world about the use of neurophysiology for cognitive workload and training

[67-75]. As the sensor hardware (e.g. battery-operated & miniaturized), signal processing algorithms (e.g. motion artifact rejection & correction), and data analytical approaches (e.g. deep learning & artificial intelligence) are improving at a rapid pace, incorporation of neurotechnology in practical training and mission critical settings are becoming more feasible. An improved understanding of the complementary use of these diverse techniques for different cognitive domains can guide that deployment process.

In this paper, we described a study design where six different neuro/physiological sensing modalities were recorded simultaneously and on the same participant cohort for six different cognitive domain tasks. The preliminary results so far indicate the commonly used signals—EEG, fNIRS, and eye-tracking—were able to differentiate controlled task difficulty and provided a biomarker modulated significantly with task difficulty. This confirms what we know from literature about these individual modalities. Our next step will be comparative analysis of modalities and sensitivity analysis of each modality separately and combined to identify potential best combinations for different tasks.

The power of physiological and neuroimaging to achieve a comprehensive and objective measure of the internal brain state while on task can revolutionize not only the way that operators are trained, but how they perform in the field. By monitoring mental workload while performing their duties, any assigned task can be dynamically altered to maintain an ideal level of workload that is neither too high nor too low. Although it may seem unrealistic to present smaller chunk tasks as described in this study, each one targets a distinct domain of cognition, which may be more involved in different physical brain areas, or even more easily measured with different imaging modalities. For example, it may be the case that risk assessment is most closely tied to heart rate variability, sustained attention is sensitive to eye movements, and working memory is in a particular area of the prefrontal cortex. By simultaneously measuring all of these, even complex, real-world operations can be accurately assessed in the wild. The strength of the methods covered here is that they are not exclusive to air traffic controllers. The basic domains are applicable to any task in different amounts and combinations, so this work is easily expandable to a wide range of fields.

When the concepts of multimodal monitoring are applied to a team of individuals, work can be shared between them to maximize the overall group efficiency. Each member may be assigned not just different overall amounts of work, but specific types that conform to their strengths. And again, even as this changes over time, the discrete assignment can be influenced by workload assessments of each domain. Multiple brains can be continuously monitored with new generation mobile neuroimaging and potentially provide information about interaction [76-78]. Looking to the future, these teams need not even be comprised of only people. Human-robot interaction is a recently burgeoning field that is now being studied with neuroimaging [79]. Studies in trust and the ability to rely on robots and AI to manage some of the work is increasingly important as we look to the future. Combining humans' ability to integrate and synthesize complex information quickly with a computer's ability to make fast calculations and reproduce tedious work indefinitely will further improve our efficiency.

Although multimodal measurements could provide new information and assessment opportunities, there are also multiple challenges and limitations ahead for these type of studies, First, simultaneous measurement with multiple types of sensors (multimodal) is difficult, it takes more time to setup each modality sensor to get good quality data, and it needs more time for preparation, system integration, time synchronization, and control during the measurement phase. Also, there could be interactions and limitations imposed on each modality due to concurrent use; for example sensor placement, space limitations, etc. Individual measurement is relatively easier, and could perform better for some mental state decoding scenarios. At the current time, single modality recording is expected to be more feasible for routine use of sensors in the field, at least initially. Another limitation is the selected sensor modality's resolution and capabilities such as the number of channels, cortical coverage, and sampling rate, which also impact the potential performance of mental state decoding performance. Newer generations of sensors are increasingly miniaturized, and higher spatial and temporal resolution is expected to improve on the said limitations.

Upon the completion of the study presented here, we will have achieved a thorough understanding of the brain and body cognitive workload assessments of a comprehensive suite of cognitive domain tasks. This can be applied not just to ATC operators, but to a wide variety of complex and real-world jobs. By using portable versions of sensors such as fNIRS and EEG, this monitoring can be taken out into the field and applied outside the lab in ecologically valid environments. In the future, this sort of everyday measurements can help the development of next generation neuroadaptive training and operating for more efficient skill acquisition and improved cognitive workload.

## ACKNOWLEDGEMENT

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## REFERENCES

[1] Parasuraman, R.Jiang, Y.: Individual differences in cognition, affect, and performance: behavioral, neuroimaging, and molecular genetic approaches. NeuroImage. **59**(1): p. 70-82. (2012)

[2] Ayaz, H.Dehais, F.: Neuroergonomics: the brain at work and in everyday life. 2018: Academic Press. (2018)

[3] Dehais, F., Karwowski, W.Ayaz, H.: Brain at Work and in Everyday Life as the Next Frontier: Grand Field Challenges for Neuroergonomics. Frontiers in Neuroergonomics. **1**(1). (2020)

[4] Hancock, P.Chignell, M.H.: Toward a Theory of Mental Work Load: Stress and Adaptability in Human-Machine Systems. Proc. IEEE SMC 1986: p. 378-383. (1986)

[5] Paas, F., Tuovinen, J.E., Tabbers, H.Van Gerven, P.W.: Cognitive load measurement as a means to advance cognitive load theory. Educational psychologist. **38**(1): p. 63-71. (2003)

[6] Braver, T.S., Cohen, J.D., Nystrom, L.E., Jonides, J., Smith, E.E.Noll, D.C.: A parametric study of prefrontal cortex involvement in human working memory. Neuroimage. **5**(1): p. 49-62. (1997)

[7] Smith, E.E.Jonides, J.: Working Memory: A View from Neuroimaging. Cognitive Psychology. **33**(1): p. 5-42. (1997)

[8] Miller, G.A.: The magical number seven, plus or minus two: Some limits on our capacity for processing information. Psychological review. **63**(2): p. 81. (1956)

[9] Klingberg, T.: Training and plasticity of working memory. Trends in Cognitive Sciences. **14**(7): p. 317-324. (2010)

[10] Sweller, J.: Cognitive Load During Problem Solving: Effects on Learning. Cognitive Science. **12**(2): p. 257-285. (1988)

[11] Sweller, J., Van Merrienboer, J.J.Paas, F.G.: Cognitive architecture and instructional design. Educational psychology review. **10**(3): p. 251-296. (1998)

[12] Debue, N.van de Leemput, C.: What does germane load mean? An empirical contribution to the

cognitive load theory. Frontiers in Psychology. **5**: p. 1099. (2014)

[13] Wickens, C.D., Hutchins, S., Carolan, T.Cumming, J.: Effectiveness of part-task training and increasing-difficulty training strategies: a meta-analysis approach. Hum Factors. **55**(2): p. 461-70. (2013)

[14] Yerkes, R.M.Dodson, J.D.: The relation of strength of stimulus to rapidity of habit ‐ formation. Journal of comparative neurology and psychology. **18**(5): p. 459-482. (1908)

[15] Mehta, R.K.Parasuraman, R.: Neuroergonomics: A Review of Applications to Physical and Cognitive Work. Frontiers in Human Neuroscience. **7**. (2013)

[16] Sibi, S., Ayaz, H., Kuhns, D.P., Sirkin, D.M.Ju, W.: Monitoring driver cognitive load using functional near infrared spectroscopy in partially autonomous cars. in 2016 IEEE Intelligent Vehicles Symposium (IV). (2016)

[17] John, M.S., Kobus, D.A.Morrison, J.G.: A multi-tasking environment for manipulating and measuring neural correlates of cognitive workload. in Human Factors and Power Plants, 2002. Proceedings of the 2002 IEEE 7th Conference on. (2002)

[18] Hart, S.G.: NASA-task load index (NASA-TLX); 20 years later. in Proceedings of the human factors and ergonomics society annual meeting. Sage Publications. (2006)

[19] Solovey, E.T., Zec, M., Garcia Perez, E.A., Reimer, B.Mehler, B.: Classifying driver workload using physiological and driving performance data: two field studies. in Proceedings of the 32nd annual ACM conference on Human factors in computing systems. ACM. (2014)

[20] Ayaz, H., Willems, B., Bunce, B., Shewokis, P.A., Izzetoglu, K., Hah, S., Deshmukh, A.Onaral, B.: Cognitive Workload Assessment of Air Traffic Controllers Using Optical Brain Imaging Sensors, in Advances in Understanding Human Performance: Neuroergonomics, Human Factors Design, and Special Populations, T. Marek, W. Karwowski, and V. Rice, Editors. 2010, CRC Press Taylor & Francis Group. p. 21-31.

[21] Harrison, J., Izzetoglu, K., Ayaz, H., Willems, B., Hah, S., Woo, H., Shewokis, P., Bunce, S.Onaral, B.: Human Performance Assessment Study in Aviation Using Functional Near Infrared Spectroscopy, in Foundations of Augmented Cognition, D. Schmorrow and C. Fidopiastis, Editors. 2013, Springer Berlin Heidelberg. p. 433-442.

[22] Harrison, J., Izzetoglu, K., Ayaz, H., Willems, B., Hah, S., Ahlstrom, U., Woo, H., Shewokis, P.A., Bunce, S.C.Onaral, B.: Cognitive Workload and Learning Assessment During the Implementation of a Next-Generation Air Traffic Control Technology Using Functional Near-Infrared Spectroscopy. Human-Machine Systems, IEEE Transactions on. **44**(4): p. 429 - 440 (2014)

[23] Ayaz, H., Shewokis, P.A., Bunce, S., Izzetoglu, K., Willems, B.Onaral, B.: Optical brain monitoring for operator training and mental workload assessment. Neuroimage. **59**(1): p. 36-47. (2012)

[24] Ayaz, H., Onaral, B., Izzetoglu, K., Shewokis, P.A., McKendrick, R.Parasuraman, R.: Continuous monitoring of brain dynamics with functional near infrared spectroscopy as a tool for neuroergonomic research: Empirical examples and a technological development. Frontiers in Human Neuroscience. **7**: p. 1-13. (2013)

[25] Ayaz, H., Willems, B., Bunce, S., Shewokis, P., Izzetoglu, K., Hah, S., Deshmukh, A.Onaral, B.: Estimation of Cognitive Workload during Simulated Air Traffic Control Using Optical Brain Imaging

Sensors, in Foundations of Augmented Cognition. Directing the Future of Adaptive Systems, D. Schmorrow and C. Fidopiastis, Editors. 2011, Springer Berlin / Heidelberg. p. 549-558.

[26] Ayaz, H., Willems, B., Bunce, S., Shewokis, P.A., Izzetoglu, K., Hah, S., Deshmukh, A.Onaral, B.: Cognitive Workload Assessment of Air Traffic Controllers Using Optical Brain Imaging Sensors, in Advances in Understanding Human Performance. 2010, CRC Press. p. 21-31.

[27] Ayaz, H., Willems, B., Bunce, S., Shewokis, P.A., Izzetoglu, K., Hah, S., Deshmukh, A.Onaral, B.: Estimation of Cognitive Workload during Simulated Air Traffic Control Using Optical Brain Imaging Sensors, in Foundations of Augmented Cognition. Directing the Future of Adaptive Systems: 6th International Conference, FAC 2011, Held as Part of HCI International 2011, Orlando, FL, USA, July 9-14, 2011. Proceedings, D.D. Schmorrow and C.M. Fidopiastis, Editors. 2011, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 549-558.

[28] Gateau, T., Ayaz, H.Dehais, F.: In silico vs. Over the Clouds: On-the-Fly Mental State Estimation of Aircraft Pilots, Using a Functional Near Infrared Spectroscopy Based Passive-BCI. Frontiers in Human Neuroscience. **12**(187). (2018)

[29] Menda, J., Hing, J.T., Ayaz, H., Shewokis, P.A., Izzetoglu, K., Onaral, B.Oh, P.: Optical Brain Imaging to Enhance UAV Operator Training, Evaluation, and Interface Development. Journal of Intelligent & Robotic Systems. **61**(1-4): p. 423-443. (2010)

[30] Ayaz, H., Cakir, M.P., Izzetoglu, K., Curtin, A., Shewokis, P.A., Bunce, S.Onaral, B.: Monitoring Expertise Development during Simulated UAV Piloting Tasks using Optical Brain Imaging. BigSky, MN, USA. doi:10.1109/AERO.2012.6187350 (2012)

[31] Hernandez-Meza, G., Slason, L., Ayaz, H., Craven, P., Oden, K.Izzetoglu, K.: Investigation of Functional Near Infrared Spectroscopy in Evaluation of Pilot Expertise Acquisition, in Foundations of Augmented Cognition, D.D. Schmorrow and C.M. Fidopiastis, Editors. 2015, Springer International Publishing. p. 232-243.

[32] Mark, J., Ayaz, H.Callan, D.: Developing a tDCS-Enhanced Dual-Task Flight Simulator for Evaluating Learning. in Advances in Neuroergonomics and Cognitive Engineering. Cham: Springer International Publishing. (2021)

[33] Izzetoglu, K., Ayaz, H., Hing, J., Shewokis, P., Bunce, S., Oh, P.Onaral, B.: UAV Operators Workload Assessment by Optical Brain Imaging Technology (fNIR), in Handbook of Unmanned Aerial Vehicles, K.P. Valavanis and G.J. Vachtsevanos, Editors. 2014, Springer Netherlands. p. 2475-2500.

[34] Ayaz, H., Curtin, A., Mark, J., Kraft, A.Ziegler, M.: Predicting Future Performance based on Current Brain Activity: An fNIRS and EEG Study. in 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC). (2019)

[35] Mark, J., Thomas, N., Kraft, A., Casebeer, W.D., Ziegler, M.Ayaz, H.: Neurofeedback for Personalized Adaptive Training, in Advances in Neuroergonomics and Cognitive Engineering: Proceedings of the AHFE 2017 International Conference on Neuroergonomics and Cognitive Engineering, July 17–21, 2017, The Westin Bonaventure Hotel, Los Angeles, California, USA, C. Baldwin, Editor. 2018, Springer International Publishing: Cham. p. 83-94.

[36] Ayaz, H., Onaral, B., Izzetoglu, K., Shewokis, P.A., McKendrick, R.Parasuraman, R.: Continuous monitoring of brain dynamics with functional near infrared spectroscopy as a tool for neuroergonomic

research: empirical examples and a technological development. Front Hum Neurosci. **7**: p. 871. (2013)

[37] Feldman, L.S., Cao, J., Andalib, A., Fraser, S.Fried, G.M.: A method to characterize the learning curve for performance of a fundamental laparoscopic simulator task: Defining “learning plateau” and “learning rate”. Surgery. **146**(2): p. 381-386. (2009)

[38] Bunce, S., Izzetoglu, K., Ayaz, H., Shewokis, P., Izzetoglu, M., Pourrezaei, K.Onaral, B.: Implementation of fNIRS for Monitoring Levels of Expertise and Mental Workload, in Foundations of Augmented Cognition. Directing the Future of Adaptive Systems, D. Schmorrow and C. Fidopiastis, Editors. 2011, Springer Berlin / Heidelberg. p. 13-22.

[39] Chiarelli, A.M., Zappasodi, F., Di Pompeo, F.Merla, A.: Simultaneous functional near-infrared spectroscopy and electroencephalography for monitoring of human brain activity and oxygenation: a review. Neurophotonics. **4**(4): p. 041411. (2017)

[40] Liu, Y., Ayaz, H.Shewokis, P.A.: Multisubject "Learning" for Mental Workload Classification Using Concurrent EEG, fNIRS, and Physiological Measures. Front Hum Neurosci. **11**: p. 389. (2017)

[41] Liu, Y., Ayaz, H.Shewokis, P.A.: Mental workload classification with concurrent electroencephalography and functional near-infrared spectroscopy. Brain-Computer Interfaces: p. 1-11. (2017)

[42] Liu, Y., Ayaz, H., Curtin, A., Onaral, B.Shewokis, P.: Towards a Hybrid P300-Based BCI Using Simultaneous fNIR and EEG, in Foundations of Augmented Cognition, D. Schmorrow and C. Fidopiastis, Editors. 2013, Springer Berlin Heidelberg. p. 335-344.

[43] Liu, Y., Ayaz, H., Onaral, B.Shewokis, P.: Neural Adaptation to a Working Memory Task: A Concurrent EEG-fNIRS Study, in Foundations of Augmented Cognition, D.D. Schmorrow and C.M. Fidopiastis, Editors. 2015, Springer International Publishing. p. 268-280.

[44] Yücel, M., Lühmann, A., Scholkmann, F., Gervain, J., Dan, I., Ayaz, H., Boas, D., Cooper, R.J., Culver, J., Elwell, C.E., Eggebrecht, A., Franceschini, M.A., Grova, C., Homae, F., Lesage, F., Obrig, H., Tachtsidis, I., Tak, S., Tong, Y., Torricelli, A., Wabnitz, H.Wolf, M.: Best practices for fNIRS publications. Neurophotonics. **8**(1): p. 012101. (2021)

[45] Quaresima, V.Ferrari, M.: Functional Near-Infrared Spectroscopy (fNIRS) for Assessing Cerebral Cortex Function During Human Behavior in Natural/Social Situations: A Concise Review. Organizational Research Methods. (2016)

[46] Curtin, A.Ayaz, H.: The Age of Neuroergonomics: Towards Ubiquitous and Continuous Measurement of Brain Function with fNIRS. Japanese Psychological Research. **60**: p. 374-386. (2018)

[47] Mckendrick, R., Parasuraman, R., Murtza, R., Formwalt, A., Baccus, W., Paczynski, M.Ayaz, H.: Into The Wild: Neuroergonomic Differentiation of Hand-Held and Augmented Reality Wearable Displays During Outdoor Navigation with Functional Near Infrared Spectroscopy. Frontiers in Human Neuroscience. **10**. (2016)

[48] von Lühmann, A., Zheng, Y., Ortega-Martinez, A., Kiran, S., Somers, D.C., Cronin-Golomb, A., Awad, L.N., Ellis, T.D., Boas, D.A.Yücel, M.A.: Towards Neuroscience of the Everyday World (NEW) using functional Near Infrared Spectroscopy. Current Opinion in Biomedical Engineering: p. 100272. (2021)

[49] Balardin, J.B., Zimeo Morais, G.A., Furucho, R.A., Trambaiolli, L., Vanzella, P., Biazoli, C.Sato,

J.R.: Imaging Brain Function with Functional Near-Infrared Spectroscopy in Unconstrained Environments. Frontiers in Human Neuroscience. **11**. (2017)

[50] Piper, S.K., Krueger, A., Koch, S.P., Mehnert, J., Habermehl, C., Steinbrink, J., Obrig, H.Schmitz, C.H.: A wearable multi-channel fNIRS system for brain imaging in freely moving subjects. NeuroImage. **85, Part 1**(0): p. 64-71. (2014)

[51] Pinti, P., Aichelburg, C., Gilbert, S., Hamilton, A., Hirsch, J., Burgess, P.Tachtsidis, I.: A Review on the Use of Wearable Functional Near-Infrared Spectroscopy in Naturalistic Environments. Japanese Psychological Research. (2018)

[52] Ayaz, H., Izzetoglu, M., Shewokis, P.A.Onaral, B.: Sliding-window Motion Artifact Rejection for Functional Near-Infrared Spectroscopy, 2010 edn., Buenos Aires, Argentina. doi:10.1109/IEMBS.2010.5627113 (2010)

[53] Gruzelier, J.H.: EEG-neurofeedback for optimising performance. I: A review of cognitive and affective outcome in healthy participants. Neuroscience & Biobehavioral Reviews. **44**: p. 124-141. (2014)

[54] Marini, F., Lee, C., Wagner, J., Makeig, S.Gola, M.: A comparative evaluation of signal quality between research-grade and wireless dry-electrode mobile EEG systems. J Neural Eng. (2019)

[55] Zander, T.O., Andreessen, L.M., Berg, A., Bleuel, M., Pawlitzki, J., Zawallich, L., Krol, L.R.Gramann, K.: Evaluation of a Dry EEG System for Application of Passive Brain-Computer Interfaces in Autonomous Driving. Frontiers in Human Neuroscience. **11**(78). (2017)

[56] Wascher, E., Reiser, J., Rinkenauer, G., Larrá, M., Dreger, F.A., Schneider, D., Karthaus, M., Getzmann, S., Gutberlet, M.Arnau, S.: Neuroergonomics on the Go: An Evaluation of the Potential of Mobile EEG for Workplace Assessment and Design. Human Factors: p. 00187208211007707. (2021)

[57] De Vos, M.Debener, S.: Mobile EEG: Towards brain activity monitoring during natural action and cognition. International Journal of Psychophysiology. **91**(1): p. 1-2. (2014)

[58] Gramann, K., Ferris, D.P., Gwin, J.Makeig, S.: Imaging natural cognition in action. International Journal of Psychophysiology. **91**(1): p. 22-29. (2014)

[59] Mullen, T., Kothe, C., Chi, Y.M., Ojeda, A., Kerth, T., Makeig, S., Cauwenberghs, G.Jung, T.-P.: Real-time modeling and 3D visualization of source dynamics and connectivity using wearable EEG. in 2013 35th annual international conference of the IEEE engineering in medicine and biology society (EMBC). IEEE. (2013)

[60] Delorme, A., Mullen, T., Kothe, C., Akalin Acar, Z., Bigdely-Shamlo, N., Vankov, A.Makeig, S.: EEGLAB, SIFT, NFT, BCILAB, and ERICA: new tools for advanced EEG processing. Comput Intell Neurosci. **2011**: p. 130714. (2011)

[61] Shaffer, F.Ginsberg, J.P.: An Overview of Heart Rate Variability Metrics and Norms. Frontiers in public health. **5**: p. 258-258. (2017)

[62] Roscoe, A.H.: Assessing pilot workload. Why measure heart rate, HRV and respiration? Biological psychology. **34**(2-3): p. 259-287. (1992)

[63] Stasi Leandro Luigi, D., Marchitto, M., Antolí, A.Cañas, J.: Testing saccadic peak velocity as an

index of operator mental workload: A partial overview. 2015. (2015)

[64] Ahlstrom, U.Friedman-Berg, F.J.: Using eye movement activity as a correlate of cognitive workload. International Journal of Industrial Ergonomics. **36**(7): p. 623-636. (2006)

[65] Rodrigo, A.H., Domenico, S.I.D., Ayaz, H., Gulrajani, S., Lam, J.Ruocco, A.C.: Differentiating functions of the lateral and medial prefrontal cortex in motor response inhibition. NeuroImage. **85, Part 1**(0): p. 423-431. (2014)

[66] Logan, G.D., Van Zandt, T., Verbruggen, F.Wagenmakers, E.J.: On the ability to inhibit thought and action: general and special theories of an act of control. Psychol Rev. **121**(1): p. 66-95. (2014)

[67] Pietro, A., Gianluca, B., Gianluca Di, F., Nicolina, S.Fabio, B.: Passive BCI beyond the lab: current trends and future directions. Physiological Measurement. (2018)

[68] Borghini, G., Aricò, P., Di Flumeri, G.Babiloni, F.: Mental States in Aviation, in Industrial Neuroscience in Aviation: Evaluation of Mental States in Aviation Personnel. 2017, Springer International Publishing: Cham. p. 29-56.

[69] Dehais, F., Duprès, A., Di Flumeri, G., Verdière, K.J., Borghini, G., Babiloni, F.Roy, R.N.: Monitoring pilot's cognitive fatigue with engagement features in simulated and actual flight conditions using an hybrid fNIRS-EEG passive BCI. IEEE SMC. (2018)

[70] Dehais, F., Dupres, A., Blum, S., Drougard, N., Scannella, S., Roy, R.N.Lotte, F.: Monitoring Pilot's Mental Workload Using ERPs and Spectral Power with a Six-Dry-Electrode EEG System in Real Flight Conditions. Sensors (Basel). **19**(6). (2019)

[71] Causse, M., Chua, Z., Peysakhovich, V., Del Campo, N.Matton, N.: Mental workload and neural efficiency quantified in the prefrontal cortex using fNIRS. Sci Rep. **7**(1): p. 5222. (2017)

[72] Izzetoglu, K., Richards, D., Ding, L., Ling, C.Willems, B.: Human Performance Assessment: Evaluation and Experimental Use of Wearable Sensors for Brain Activity Measures. in 19th International Symposium on Aviation Psychology. (2017)

[73] Çakır, M.P., Vural, M., Koç, S.Ö.Toktaş, A.: Real-Time Monitoring of Cognitive Workload of Airline Pilots in a Flight Simulator with fNIR Optical Brain Imaging Technology, in Foundations of Augmented Cognition: Neuroergonomics and Operational Neuroscience. 2016. p. 147-158.

[74] Mullen, T.R., Kothe, C.A.E., Chi, Y.M., Ojeda, A., Kerth, T., Makeig, S., Jung, T.Cauwenberghs, G.: Real-time neuroimaging and cognitive monitoring using wearable dry EEG. Biomedical Engineering, IEEE Transactions on. **62**(11): p. 2553-2567. (2015)

[75] Gramann, K., Fairclough, S.H., Zander, T.O.Ayaz, H.: Editorial: Trends in Neuroergonomics. Frontiers in Human Neuroscience. **11**(165). (2017)

[76] Nozawa, T., Kondo, M., Yamamoto, R., Jeong, H., Ikeda, S., Sakaki, K., Miyake, Y., Ishikawa, Y.Kawashima, R.: Prefrontal Inter-brain Synchronization Reflects Convergence and Divergence of Flow Dynamics in Collaborative Learning: A Pilot Study. Frontiers in Neuroergonomics. **2**(19). (2021)

[77] Stuldreher, I.V., Thammasan, N., van Erp, J.B.F.Brouwer, A.-M.: Physiological Synchrony in EEG, Electrodermal Activity and Heart Rate Detects Attentionally Relevant Events in Time. Frontiers in

Neuroscience. **14**(1257). (2020)

[78] Liu, Y., Piazza, E.A., Simony, E., Shewokis, P.A., Onaral, B., Hasson, U.Ayaz, H.: Measuring speaker–listener neural coupling with functional near infrared spectroscopy. Scientific Reports. **7**: p. 43293. (2017)

[79] Sheridan, T.B.: Human-Robot Interaction: Status and Challenges. Hum Factors. **58**(4): p. 525-32. (2016)