

THE RELATIONSHIP BETWEEN REAL-TIME EEG ENGAGEMENT, DISTRACTION AND WORKLOAD ESTIMATES AND SIMULATOR-BASED DRIVING PERFORMANCE

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Summary: Identifying potentially impaired drivers is often dependent upon using cognitive testing from a controlled environment (clinic, laboratory) to predict behavior in a dynamic and unpredictable real world driving environment. The goal of this study was to determine the feasibility, and validity, of using a wireless EEG system to ultimately differentiate between impaired and unimpaired drivers. We utilized the B-Alert X10 portable wireless EEG/ECG system and applied previously validated EEG algorithms estimating engagement, workload, and distraction within a sample of normal control (n = 10) and HIV seropositive individuals (n = 14). Participants underwent a 30-minute fully interactive driving simulation. Overall, the HIV+ group evidenced significantly higher distraction during the simulation. When grouped according to poor and good performers on the simulation (regardless of HIV serostatus), those performing worse on the simulation had higher distraction, with a trend for lower workload, levels. We then examined EEG profiles immediately preceding a crash. Prior to a crash, participants evidenced a significant increase in distraction ~ 10-14 seconds leading up to the crash; the greatest increase was seen in the HIV+ group. These preliminary data support the potential utility of using EEG data in patient populations to identify individuals who might be at risk for impaired driving.

INTRODUCTION

Despite significant advances in neuroscience research, little is known regarding the cognitive mechanisms of real world functioning (Burgess et al., 2006). Most studies collect neuropsychological (NP) data in a setting where distractions are minimized and individuals complete one task at a time with support from the examiner, and then try to predict real-world functioning (a chaotic environment with conflicting priorities, time pressures, and opportunities for engagement to wane) (Marcotte, Scott, Kamat, & Heaton, 2009). One recent approach, the application of EEG-based cognitive state algorithms to capture neurophysiological data during various activities, has thus far had two critical limitations: 1) the inability to handle dynamic real world conditions (e.g., driving), and 2) a focus only on non-neurologic populations.

This study examines the feasibility, and preliminary validity, of adapting Advanced Brain Monitoring's (ABM) B-Alert @ X10, portable, wireless EEG system and cognitive state algorithms (engagement, distraction, workload) for use "in the wild" – in a driving simulator, with both healthy and neurologically compromised drivers (individuals with HIV-associated neurocognitive disorders [HAND]). HAND is an important population because 1) HIV is now a chronic condition, initially affecting individuals in young/middle age, 2) HAND remains prevalent and affects everyday functioning (Heaton et al., 2004), including automobile driving

(Marcotte et al., 1999; Marcotte et al., 2006; Marcotte et al., 2004), and 3) as with other conditions, clinic-based NP assessments only modestly predict who will, or will not, fail real world tasks (Marcotte & Scott, 2009; Reger et al., 2004).

The previously validated EEG-based algorithms for engagement, workload, and distraction, as well as a set of individual data from three tasks to adjust centroids, enables both individualization (required due to the complexity of individual variability in EEG) and generalization (required to apply the algorithm across subjects and tasks) (Berka et al., 2007; Johnson et al., 2011). Based on the development process of these algorithms, engagement is associated with active attention/vigilance constructs, distraction is the inability to maintain passive attention, and workload is primarily focused on working memory load and processing. These algorithms have proven robust in multiple real world validation studies (Berka et al., 2007; Berka et al., 2005; Stevens, Galloway, & Berka, 2006; Stevens, Galloway, & Berka, 2007a; Stevens, Galloway, & Berka, 2007b).

Driving provides a rich environment for evaluating real-world cognition using EEG algorithms - it is characterized by monotony contrasted with elevated workload, overlearned behaviors and novel responses, multi-tasking, risk-assessment, and time pressure, with salient and immediate consequences (e.g., crash or ticket).

METHOD

Subjects

Participants (n = 24) were active drivers (at least 1000 miles in the last year) with a current driver's license. Exclusion criteria include a history of loss of consciousness greater than 30 minutes, current substance dependence, psychosis, diagnosis of a cardiovascular, sleep, or pulmonary disorder, and central nervous system opportunistic infections or neurologic disease other than HIV infection. For this study, we also excluded individuals with reported diagnoses of Attention Deficit Hyperactivity Disorder and anxiety-related disorders, since the effect of these conditions on the algorithms is unclear. All participants were recruited from the UCSD HIV Neurobehavioral Research Program (HNRP) in San Diego.

The sample consisted of 10 HIV-seronegative controls and 14 HIV-seropositive individuals who were similar with respect to age (49.1 vs. 52.6 years, respectively), education (14.9 vs. 14.1 years), and gender (60% vs. 86% male).

Simulated Driving

Participants complete a PC-based driving simulation (STISIM software) consisting of a PC computer, steering wheel, and accelerator/brake pedals, auditory feedback (e.g., engine noise), with the driving environment (roadway, cars, buildings, pedestrians) displayed on a 52" plasma screen. The simulation, based upon a version previously shown to be predictive of on-road performance in an HIV+ population (Marcotte et al., 2004), took approximately 30 minutes. Participants were instructed to get to a location as soon as possible, but to follow traffic laws. The simulation included monotonous, uneventful and low-load driving scenarios, as well as

highly demanding events (e.g., intersections, crash avoidance, freeway merges). Participants also needed to respond to occasional divided attention tasks in the corner of the screen.

To minimize the novelty of the tests, participants completed a pretest training session of approximately 10 minutes to familiarize them with the hardware and tasks they were to encounter. For this early analysis, the primary simulator outcome was the number of crashes during the simulation run.

EEG acquisition

The B-Alert X10 headset (Advanced Brain Monitoring, Inc, Carlsbad CA) was used to acquire 9 channels of EEG and ECG. The sensor locations for the EEG included: Fz, Cz, POz, F3, F4, C3, C4, P3, and P4. Data were sampled at 256 Hz with a band pass from 0.5 Hz to 65 Hz (at 3 dB attenuation) obtained digitally with Sigma-Delta A/D converters. The RF link was frequency-modulated to transmit at a rate of 57 kBaud in the 915 MHz ISM band. By utilizing the bidirectional mode, the firmware allowed the host computer to initiate impedance monitoring of the electrodes, select the transmission channel (so two or more headsets can be used in the same room), and monitor battery power of the headset. Data were acquired across the RF link on a host computer via an RS232 interface. Data acquisition software then stored the EEG data on the host computer. The proprietary acquisition software used also includes artifact decontamination algorithms for eye blink, muscle movement, and environmental/electrical interference such as spikes and saturations.

Alertness and memory profiler. In order to utilize the cognitive state algorithms for engagement and workload, a set of three neurocognitive assessments are required with simultaneous/-synchronized EEG (Johnson et al, 2011; Berka 2004), which are administered through the Alertness and Memory Profiler software. This custom software was developed to time the presentation and capture the response of each stimulus in each NP task, while creating a file that stored the simultaneously acquired electroencephalographic (EEG) signals and marking the file at presentation of the stimuli and at response with the type of response. Three vigilance tasks were administered. The NP vigilance tasks included an auditory psycho-vigilance task, a visual psycho-vigilance task, and a 20-min three-choice vigilance task. For the auditory psycho-vigilance task, an auditory tone every 2 seconds prompted the participant to tap in time with the noise for 5 min. The visual psycho-vigilance task presented a 10 cm circular target image for 200 ms in the center of the computer monitor, repeated every 2 s for 5 min; the subject was asked to tap the spacebar in time with the target image.

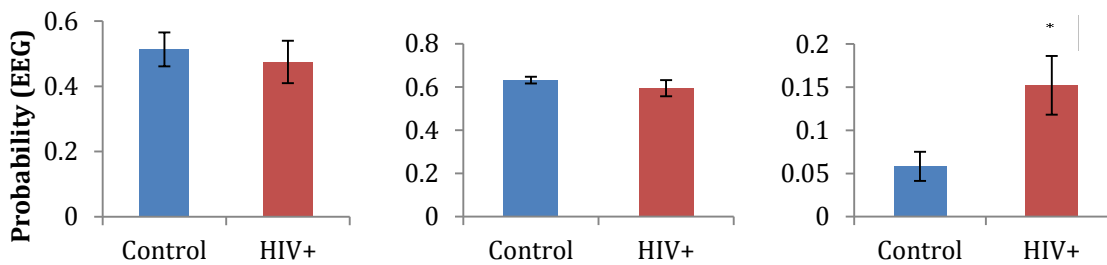
The three-choice vigilance task requires subjects to discriminate one primary (70% occurrence) from two secondary (30% occurrence) geometric shapes with a stimulus presentation interval of 200 ms over a 20-minute test period. Participants were instructed to respond as quickly as possible to each stimulus presentation. A training period was provided prior to the beginning of the task to minimize practice effects. During the first 5 min of the session, the inter-stimulus interval ranged from 1–3 s, while the middle 10-min period had an inter-stimulus interval range of 1–6 s. During the final 5 min, the inter-stimulus interval range was 1–10 s. Participants were instructed to select the left arrow to indicate target stimuli, and the right arrow to indicate non-target stimuli.

These three tasks are then used to individualize the algorithms by adjusting the centroids, to provide engagement, workload, and distraction probabilities. Engagement is optimized based on the 3CVT performance for the first five minutes, requiring active vigilance and attention, as well as decision-making. Distraction is optimized based on the auditory vigilance task, and is sensitive to failures in passive attention required for that basic task. The overall algorithm is a four-class (sleep onset, distraction, low/passive vigilance, and high engagement). Additional details may be found in Johnson et al, 2011. Workload does not require the benchmark AMP tasks to optimize across individuals, and was developed using digit span tasks, and is thus primarily accessing working memory load capacity and effort.

RESULTS

EEG Algorithms between Patient vs. Non-Patient Groups

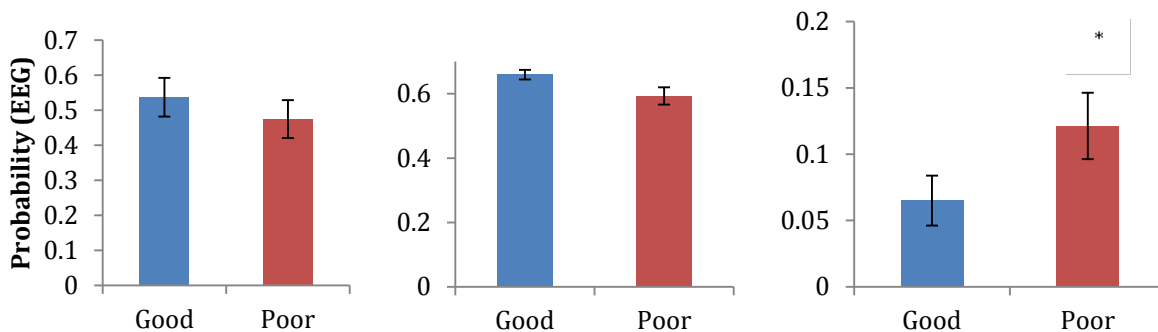
There was no clear difference in EEG engagement ($p = .18$) or workload profiles ($p = .23$), over the entire simulation, based upon HIV serostatus alone (Figure 1a, b respectively). In contrast, the HIV+ evidenced higher distraction levels ($p < 0.05$ (Figure 1c)) than controls.



Figures 1a, b, c. Mean Engagement, Workload and Distraction algorithm profiles, by HIV status

EEG Algorithms and Simulator Performance

When participants were classified into those who did better (≤ 2 crashes) vs. worse (> 2 crashes; $n = 8$) on the driving simulation (Figure 2a, b, c), there was significant separation on Distraction scores, $p = 0.02$), with a trend for workload ($p = 0.10$); there was no difference in Engagement levels ($p = .56$).



Figures 2a, b, c. Mean Engagement, Workload and Distraction algorithm profiles, by better vs. worse performance on the driving simulation

Engagement and Workload Preceding Crashes

Participants had crashes at different portions of the 30-minute simulation. For this preliminary examination of the data, we grouped the crashes together and examined matching sections in which a participant did not have a crash. We then plotted the engagement, workload and distraction algorithm values for the 20 seconds preceding, and 20 seconds following, the point of the crash. There was no clear separation of engagement levels prior to the crash. Distraction, on the other hand, is elevated (by approximately 80%) in the 8-14 seconds prior to the crash, while Workload also decreases 20-25% from 10-16 seconds prior to the crash .

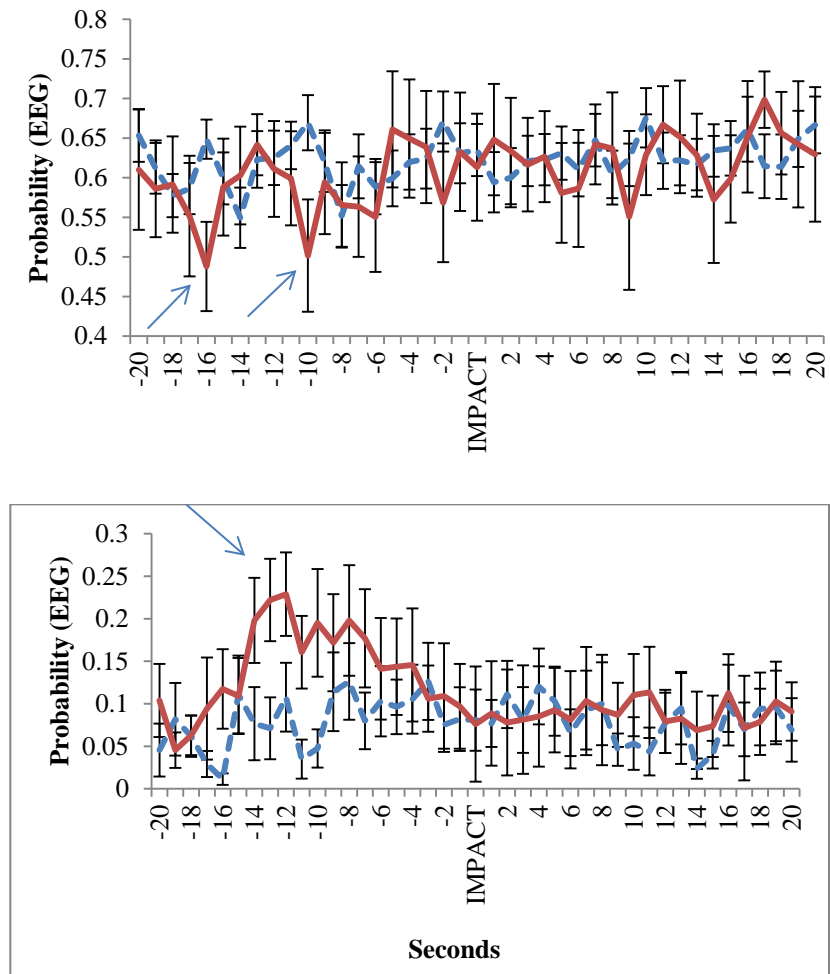
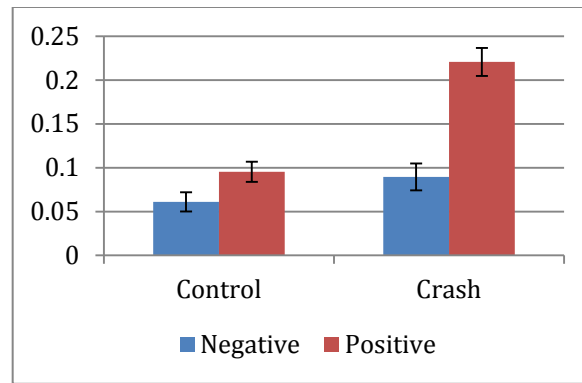


Figure 3. Mean a) Workload and b) Distraction algorithm profiles near crash events. X-axis values indicate seconds preceding and following the crash (“impact”)

There was an interaction between Distraction levels and HIV status on simulator performance, with the HIV+ group demonstrating a significantly greater increase in Distraction scores prior to the crash (Figure 3).



Figures 4. Distraction scores prior to the crash, stratified by HIV serostatus

DISCUSSION

The current results provide preliminary evidence of the feasibility of collecting wireless EEG data during dynamic simulator runs, and syncing algorithmic estimates of engagement, workload, and distraction to simulator events, such as crashes.

Notably, while the HIV group evidenced higher Distraction scores across the entire simulation, this did not mask a robust relationship between elevated Distraction scores immediately preceding a crash, suggesting that changes in these algorithms are not solely the product of neurologic disease. This also provides preliminary data supporting the potential utility of these methods in individuals with brain disorders.

Clarification of the mechanisms of the increased distraction 10-14 seconds prior to a crash awaits more detailed analyses in larger samples. We are continuing to accrue additional participants, and will also include wireless EEG data collection while they undergo a structured on-road drive, in order to determine whether the current algorithms relate to real-world driving performance. The ultimate goal is to determine whether these algorithms might provide a sensitive measure of driving-related cognitive deficits – perhaps detecting impairments that are not readily observable during a brief sampling of on-road or simulator-based driving behavior.

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