EEG Correlates of Task Engagement and Mental Workload in Vigilance, Learning, and Memory Tasks

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实验背景
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Introduction: The ability to continuously and unobtrusively monitor levels of task engagement and mental workload in an operational environment could be useful in identifying more accurate and efficient methods for humans to interact with technology. This information could also be used to optimize the design of safer, more efficient work environments that increase motivation and productivity. ***Methods:*** The present study explored the feasibility of monitoring electroencephalographic (EEG) indices of engagement and workload acquired unobtrusively and quantified during performance of cognitive tests. EEG was acquired from 80 healthy participants with a wireless sensor headset (F3-F4,C3-C4,Cz-POz,F3-Cz,Fz-C3,Fz-POz) during tasks including: multi-level forward/backward-digit-span, grid-recall, trails, mental-addition, 20-min 3-Choice Vigilance, and image-learning and memory tests. EEG metrics for engagement and workload were calculated for each 1-s of EEG. ***Results:*** Across participants, engagement but not workload decreased over the 20-min vigilance test. Engagement and workload were significantly increased during the encoding period of verbal and image-learning and memory tests when compared with the recognition/recall period. Workload but not engagement increased linearly as level of difficulty increased in forward and backward-digit-span, grid-recall, and mental-addition tests. EEG measures correlated with both subjective and objective performance metrics. ***Discussion:*** These data in combination with previous studies suggest that EEG engagement reflects information-gathering, visual processing, and allocation of attention. EEG workload increases with increasing working memory load and during problem solving, integration of information, analytical reasoning, and may be more reflective of executive functions. Inspection of EEG on a second-by-second timescale revealed associations between workload and engagement levels when aligned with specific task events providing preliminary evidence that second-by-second classifications reflect parameters of task performance.

Keywords: Cognition, neuroergonomics, military operations, brain monitoring, human-computer interface, neurophysiology, psychophysiology.

INFORMATION OVERLOAD is a fact of life in the contemporary global networked society. Potentially rich sources of data are underutilized because they cannot be organized efficiently enough to accommodate the capacity of the human information processing system. One approach to expanding the capacity of processing is to radically rethink the design of human-machine system interfaces to optimize the flow and exchange of data between humans and machines. This approach, termed "neuroergonomics," is an interdisciplinary area of research and practice that integrates understanding of the neural bases of cognition and behavior with the design, development and implementation of technology (21,29,34,35). The vision of neuroergonomics is to use knowledge of brain-behavior relationships to optimize the design of safer, more efficient work environments that increase motivation and productivity.

One promising avenue of research in neuroergonomics involves developing the capability to continuously monitor an individual's level of fatigue, attention, task engagement, and mental workload in operational environments using physiological parameters (2,3,19,22,32,44,46,47,55). These physio-cognitive monitoring systems have a wide range of potential applications that could significantly enhance performance, productivity, and safety in military, industrial, and educational settings, including evaluating alternative interface designs, enhancing skill acquisition, and optimizing the ways humans interact with technology (35).

The new field of "augmented cognition" takes psychophysiological measurement to the next level by integrating continuous monitoring into closed-loop systems. By using the operator states as inputs, adaptively automated systems respond to user overload or underload, and react appropriately (42,43). Physiological indicators of user overload or underload can be used to trigger greater information dissemination or task reallocation. Preliminary investigations suggested the possibility that performance could be enhanced in these closed-loop model systems (13,31,50–52,55).

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Operational Applications of Cognitive Performance Enhancement Technologies was supported through the Office of Naval Research (ONR), Arlington, VA; the U.S. Army Medical Research and Materiel Command (USAMRMC), Ft. Detrick, MD; the Eye-Com Eye-tracker Research Program, Reno, NV; and through an unrestricted educational grant from Cephalon, Inc.

Heart rate variability, oculomotor activity (EOG), pupilometry, functional near infrared imaging (fNIR) and galvanic skin response have been employed to detect cognitive state changes; however, the electroencephalogram (EEG) is the only physiological signal that has been shown to accurately reflect subtle shifts in alertness, attention and workload that can be identified and quantified on a second-by-second time-frame. Significant correlations between EEG indices of cognitive state changes and performance have been reported based on studies conducted in laboratory, simulation and operational environments (2,11,12,17,18,26–28,36,45,47,56,57).

The conventional methods employed to analyze the EEG generally involve computation of the power spectral densities (PSD) within the classically defined frequency bands including alpha, beta, theta, delta, and gamma or ratios between these frequency bands (19,46,47,55). Alternatively, the amplitudes of the N100 and P300 components of the event-related potential (ERP) have been employed in some cognitive assessment models (21,22,49), however, the use of the ERP for operational applications currently has several limitations including the requirement for introducing "probe" stimuli into real-world tasks to elicit the potentials and the need for averaging of single trials across scalp sites or over time.

The EEG PSD bands or ERP component measures are then used as inputs to classifier models to allow identification and classification of cognitive states such as mental workload, attention, engagement, executive function, and verbal or spatial memory. A variety of linear and nonlinear classifier models have been employed including linear, quadratic, and logistic discriminant function analysis (DFA), artificial neural networks (ANN), and support vector machines (13,15,20,41,54,57).

Prinzel and colleagues at NASA Langley and Old Dominion University (30,38) developed an EEG-engagement index based on beta power (13–22 Hz) divided by alpha power (8–12 Hz) plus theta power (5–7 Hz) and applied it in a closed-loop system to modulate task allocation. They reported improved performance in a vigilance task when the EEG-engagement index was used to drive changes in the stimulus presentation (16,30,39).

Wilson and colleagues at Wright-Patterson AFB, OH, integrated 38 measures derived from EEG, EOG, and heart rate and reported that an artificial neural network (ANN) classified level of operator workload and verbal/spatial working memory with accuracy between 85–90% in an unmanned combat air vehicle simulation (41,55,57). Using the same 38 measures as training data, Russell and Wilson compared their ANN with linear, quadratic, and logistic discriminant function analyses. Although the ANN provided the most accurate model, the DFAs classified with between 85–89% accuracy for workload and verbal/spatial working memory.

Gevins (17–19) and Smith (44) reported frontal midline EEG theta activity (5–7 Hz) increases during high task-load conditions and attenuated alpha activity (8–12 Hz) proportional to increasing cognitive load during performance of an n-back working memory task. They suggested that these data could be combined in a multivariate approach individualized for each subject to indicate the extent to which a set of task demands activates the cortex during performance of the task. The utility of individualized models has been suggested by other investigators (1,14,52,55).

Although individualized models can provide highly accurate classifications of cognitive state, they may be impractical in operational environments due to the additional time required for personnel to obtain the model data and the computer processing time and capacity required to create complex models such as those required by ANNs. In the present study, the goal was to develop a method for quantifying mental workload that generalized across tasks and participants.

Herein we present an integrated hardware and software solution for acquisition and real-time analysis of the EEG, including an easily applied wireless EEG system designed with the goal of future operational deployment. The analytical approach employs linear and quadratic DFA to identify and quantify cognitive state changes using model-selected relative and absolute power spectra variables from 1–40 Hz. This modeling technique allows simultaneous selection of multiple EEG characteristics across brain regions and spectral frequencies of the EEG for detecting cognitive state correlates in both real-time and off-line analysis.

This method has previously been applied to classify 1-s segments of EEG to identify drowsiness-alertness (23–25), mental workload (2,4,33), spatial and verbal processing in simple and complex tasks (3), to characterize alertness and memory in patients with sleep apnea (7,53), and to identify individual differences in susceptibility to the effects of sleep deprivation (5). The system has also been integrated into real-time, closed-loop automated computing systems to implement dynamic regulation and optimization of performance during a driving simulation task and in the Aegis C2 and Tactical Tomahawk Weapons simulation environments (3,4,6,50).

There are several challenges that must be overcome by developers of cognitive state monitors. First, it is necessary to define a set of relatively pure tasks that consistently elicit the targeted cognitive states to provide training data for the model and to validate the methods for cognitive monitoring. Validation of cognitive state measures generally involves experimental manipulation of task demands to induce cognitive state changes, objective measurement of performance metrics (e.g., accuracy, reaction time) and subjective measures that allow participants to describe their perceived level of difficulty as well as the amount of effort exerted in a given task. The cognitive state measures must also be validated across participants and adjusted to account for individual differences when required.

This paper presents evidence for the utility of two EEG-based measures of cognitive states, task engagement, and mental workload. Both measures increase as a function of increasing task demands but the engagement measure tracks demands for sensory processing and attention resources while the mental workload index was developed as a measure of the level of cognitive processes generally considered more the domain of executive function.

METHODS

EEG was acquired from a total of 80 participants including 13 studied at the Lockheed Martin Advanced Technology Lab and used for model development. All study protocols were approved in advance by the certified independent Institutional Review Boards, Chesapeake Research Review, Inc and the Biomed IRB, Inc. The data from 67 participants used for cross validation were acquired at the Advanced Brain Monitoring (ABM) human subject testing facility using protocols for 3 studies approved in advance by the Biomed IRB. Each subject provided written informed consent before participating.

During data acquisition all participants wore the wireless sensor headset that acquired EEG from the bi-polar sensor sites F3-F4, C3-C4, Cz-POz, F3-Cz, Fz-C3, and Fz-POz. All subjects completed the three baseline tasks, a three-choice vigilance task, and 5 min of eyes open and eyes closed.

The data used to develop and validate the workload gauge were acquired from 13 subjects during 5 tasks developed by Lockheed Martin. The tasks were performed in the following order: grid, forward digit span, mental arithmetic, backward digit span, and trails. Each task had between three and six levels of difficulty. For example, during the backward digit span, level one required the subject to memorize 2 digits and a total of 20 digit sets were presented. Level two was 4 digits and 12 digit sets, level three was 6 digits and 8 digit sets, and level four was 8 digits and 5 digit sets. Participants were allowed to self-pace with respect to the time needed to complete each problem.

For the Addition task, participants were asked to add two numbers with varying numbers of digits in addends, and report the sum by typing digits using the keyboard. This task required participants to employ working memory and executive function resources. Difficulty was manipulated by increasing the number of digits to be added at each level.

Grid location: During Grid location, an N $\times$ N grid of squares where N ranged from 3–6, was presented with some grids containing missiles. The grid with missiles was then replaced by an empty grid and participants were prompted to identify which squares contained missiles by clicking in the squares in an empty grid. This task required spatial working memory resources with memory load manipulated at each level by increasing the grid dimensions and the number of missiles to be remembered.

Trail-making task: In the Trail-making (Trails) task, participants were presented with a series of labeled dots on a computer screen, and asked to "draw a trail" by clicking on the dots in series. The labels were numbers or letters or combinations of both, and participants were required to click on them in order. The order codes were more complex for the level two and three tasks. This task required participants to employ spatial memory and executive function.

Digit span: In Forward digit span (FDS), a series of single digits of increasing lengths were presented followed by an empty box prompting the participant to enter the digits in the box in the order presented. Similarly, the Backwards digit span (BDS) presented a series of single digits of increasing lengths and required entering digits in the reverse order from the one presented. For both FDS and BDS, the task difficulty was manipulated by increasing the number of digits at each level. Two objective performance measures were derived, complete correct answers for each task and level, and partially correct answers. For example, seven of nine correct numbers in a 9-digit forward digit span resulted in a 0.78 partial correct score and a complete correct answer score of 0.

Subjective estimates of workload were acquired from the 13 participants evaluated in the Lockheed Martin study using a survey administered to the participant following each difficulty level of each task. Responses to the following questions were rated on a 100-point scale: How much mental energy did you exert on this task level (almost none. . . a whole lot)? Objectively, how difficult was this task level (quite easy. . . extremely difficult)? and, How much attention did you focus on this task level (very little. . . I was extremely focused)?

For the cross validation data set, participants completed a 20-min 3-choice-vigilance test (n = 65), an image learning and recognition memory test followed by an interference session (n = 50) where previously learned items appear but are no longer in the learning set, a verbal paired associate learning and memory test (n = 50) and multi-level forward and backward digit-span tests (described previously) (n = 17).

3-Choice Vigilance Task: The 3-Choice Vigilance Task (3C-VT) incorporates features of common neuropsychological tests of vigilance, including simple or choice reaction time tests and continuous performance tests (40). The 3C-VT requires participants to discriminate primary (presented 70% of the time) from two secondary geometric shapes presented for 0.2 s and respond over a 20-min test period. A training period is provided prior to testing to minimize practice effects.

Image, verbal and interference learning and memory tests: These tests evaluate attention, distractibility and recognition memory for images, image-number pairs or word pairs. During the encoding session, a group of 20 images are presented twice. The recognition session presents the 20 training images randomly interspersed with 80 additional images. Participants must indicate whether or not the image was in the training set. Five equivalent image categories were developed (animals, food, household goods, sports, and travel). In the Standard Image Recognition, the subject must memorize 20 images and identify the 20 training images amid 80 previously unseen testing images. For the Interference Image Recognition, a set of 20 new images must be memorized and distinguished from the first set of training images from the Standard encoding session and 60 images previously displayed in the Standard recognition session. The Verbal Paired Associate test (VPA) is identical to the Standard, substituting word pairs for images. Easy (e.g., black-white, dog-cat) and difficult (e.g., table-horse, fence-towel) word pairs are included in each test.

The 67 participants in the studies conducted at ABM completed a subjective ratings questionnaire after each level of the FDS and BDS. Each participant was asked to rate the difficulty of the level they just completed on a 5-point scale: very difficult, difficult, neither easy nor difficult, easy, or very easy. Subjective reporting was simplified in order to decrease the amount of time needed to complete all levels of the tests. All testing done at ABM required consistent time constraints for performance.

The selection of the bi-polar sites F3-F4, C3-C4, Cz-POz, F3-Cz, Fz-C3, and Fz-POz was made based on results from a previous experiment when mono-polar recordings were acquired and bi-polar recordings were calculated (Berka C. Unpublished observations; 2005). The objective of the analysis was to limit the sensors (seven) and channels (six) to ensure the sensor headset could be applied within 10 min. Bi-polar recordings were selected in order to reduce the potential for movement artifacts that can be problematic for applications that require ambulatory conditions in operational environments.

Each EEG channel was sampled at 256 samples per second and analyzed using signal processing techniques that identified and either decontaminated or excluded 1-s periods ("epochs") with artifact. Prior to all other signal processing, a 60-Hz notch filter was applied to remove environmental artifact. Spikes, amplifier saturation and excursions that related to movement were analyzed in the time domain. Spikes and excursions were identified when the EEG amplitude changed significantly (e.g., $> 40\ \mu V$) over short durations (e.g., ~12–27 ms). Amplifier saturation was recognized when the change in amplitude between two data points exceeded predefined thresholds (e.g., 440 μV) or the EEG amplitude approached the maximum/minimum of the amplifier dynamic range. These thresholds were established based on the unique characteristics of the amplifier circuit that was utilized. The data points associated with these artifacts were used in a later step to decontaminate the EEG. The EEG was then deconstructed using a wavelets transformation into the 0–2, 2–4, 4–8, 8–16, 16–32, 32–64, and 64–128 Hz wavelets bands. The wavelets power in the 64–128 Hz band was used to identify epochs with excessive muscle activity (EMG) that were rejected from further analysis.

To detect eye blinks, a linear discriminant function analysis was employed which uses the absolute value of the 0–2, 2–4, 4–8, 8–16, and 16–32 Hz wavelet coefficients from the 50th, 40th 30th, 20th, and 10th data points before and after the target data point from FzPOz and CzPOz as variables to classify each data point as an eye blink, theta wave, or non-eye blink. Selected data from healthy, sleep-deprived subjects were used to train the DFA to recognize eye blinks, theta waves, or non-eye blinks.

Multiple data points classified as eye blinks were used to identify the eye blink region. The eye blink region is established based on a fixed distance before the start (e.g., 50 data points) and after the end (e.g., 50 data points) of the blink. Decontamination of eye blinks was accomplished by computing mean wavelet coefficients for the 0–2, 2–4, and 4–8 Hz bins from nearby non-contaminated regions and replacing the contaminated data points. The EEG signal was then reconstructed using all wavelets bands except 64–128 Hz. The data points previously associated with spikes, excursions, or saturation were replaced with zero values at zero crossing before and after spikes, excursions, and saturations. Finally, EEG absolute and relative power spectral density (PSD) variables for each 1-s epoch were computed using a Fast-Fourier transform applied using a 50% overlapping Kaiser window ($\alpha = 6.0$). The PSD values were scaled to accommodate the insertion of zero values as replacements for the artifact.

EEG Metric for Task Engagement

For the engagement measure, a four-class quadratic DFA was derived for each participant (10,15). The four-class model was constructed using absolute and relative power spectra variables from Fz-POz and Cz-POz obtained using stepwise regression on a database of over 100 participants under fully rested and sleep-deprived conditions. The model was individualized for each participant using DFA coefficients derived during three 5-min baseline tasks described previously. The first 5 min of 3-choice vigilance task, eyes open, and eyes closed baseline sessions were used to establish the model for output classes high engagement, low engagement, and relaxed wakefulness. The individualized coefficients for the fourth output class, sleep onset, were derived using regression equations based on the absolute and relative power data from the subject's three baseline conditions. One regression equation was used for each variable/coefficient in the four-class model. The regression equations were developed using a database of baseline and sleep onset data from healthy, sleep-deprived subjects.

EEG Metric for Mental Workload

The workload classifier was developed using a linear DFA with two classes, low and high mental workload (10,15). The approach for development of the workload measure was similar to that employed for deriving the engagement measure in that the absolute and relative power spectra variables were obtained using stepwise regression on EEG data from C3-C4, Cz-PO, F3-Cz, Fz-C3, and Fz-PO. (F3-F4 was excluded from analysis because of disproportionate amount of EMG that was identified at this site.) Different combinations of low and high difficulty levels of the mental arithmetic, grid location, and digit-span tasks were evaluated as training data to derive two-class workload classifiers (i.e., low and high). Comparisons of classification results for both the training and cross-validation data were used to select one workload model that generalized across individuals. The final set of EEG variables selected to provide the optimal classification of EEG-engagement and mental workload are listed by channel and frequency bin in **Table I**. For example, the engagement DFA model uses a total of seven model-selected vari-

TABLE I. EEG VARIABLES USED FOR COMPUTATION OF ENGAGEMENT AND WORKLOAD.

	1 – 4 Hz	5 – 7 Hz	8 – 13 Hz	14 – 24 Hz	25 – 40 Hz
Engagement - Absolute and Relative PSD Variables Selected (1 Hz bins)					
FzPOz	0	0	0	1	6
CzPOz	1	2	5	2	6
Workload Classifier - Absolute and Relative PSD Variables Selected					
C3C4	1	0	2	2	2
CzPOz	0	0	0	2	5
F3Cz	0	3	1	0	1
F3C4	1	0	1	1	0
FzC3	1	0	0	1	1
FzPOz	1	0	1	1	2

ables from channel FzPOz, including one in the 14–24 Hz and 6 in the 25–40 Hz bins (absolute and relative PSD).

For each epoch of EEG, the four-class DFA and workload DFA each provided a final classification (e.g., winning class) as well as the probability of the correct classification for each class. The present study used the probability of high engagement and high workload associated with each epoch as the classifier output. The probability values were chosen because the goal was to identify a gradient of results in multi-level tasks and not to simply class each epoch as high or low.

Rationale for Development and Validation of the EEG-Mental Workload Index

The investigators had previously reported that the EEG-engagement measure was correlated with task demands including the level and complexity of stimulus processing and the requirement for allocation of attentional resources (2,33). EEG-engagement was found to be directly correlated with task load in simple vigilance and memory tasks and in more complex simulation tasks including the Warship Commander, a simulated naval command and control task and in an Aegis radar operations simulation environment (2,4). Subsequent applications of the EEG-engagement metric revealed that it did not increase as a function of increasingly difficult mental arithmetic, during increasingly complex analytical reasoning, during multiple levels of difficulty in a Sternberg verbal memory task or during the five levels of the forward or backward digit span test, suggesting the need for development of a new EEG metric for workload. This paper presents evaluations of the engagement index and the new mental workload index across multiple tasks, participants, and conditions.

The rationale for using simple tasks to calibrate the classifiers and build the model is two-fold. First, it is difficult to isolate pure cognitive states in complex operational tasks to provide adequate training data for any model. Second, this approach is built on the assumption that the cognitive states involved in simple and complex tasks can be distilled into fundamental processes such as attention, working memory, and mental workload, and that the classifiers will translate across operational environments. Previous work by the investigative team showed that models created using simple tasks were valid when used for more complex operational simulations (2-4,50); however, these studies were reported as preliminary with the caveat that extensive validation is required before the classification models can be useful in operational environments.

Three methods were used to validate physiological measures of mental workload. The first is inherent in the task design; the tasks used to validate must include incrementally increasing levels of difficulty to elicit increasing levels of mental workload required by the participant. The second method of validation is to correlate objective measures of task performance with the EEG Index. The final method is to compute the correlations of the EEG Indices with the subjective reports. All three methods have strengths and weaknesses, but arguably each can contribute to the overall validation of the EEG metrics.

RESULTS

Fig. 1 presents the mean workload levels as classified by the EEG model for each level of difficulty for the Grid, Addition, FDS and BDS, and Trails tasks with the associated mean subjective ratings for each level of each task. EEG workload levels accurately tracked the intended pattern of the task design and the subjective ratings for all tasks except the Trails task. **Fig. 2** presents the same EEG workload data with the associated mean objective performance scores. As expected, performance decreases as a function of task difficulty with the exception of the Trails task where participants achieved perfect performance on all three levels of the Trails. In the Trails task, the EEG workload was more closely aligned with the objective performance measure than the task design levels or subjective rating levels. All participants achieved a perfect score for the Trails task because it was impossible to complete Trails task until the participant responded correctly.

The mean EEG-engagement values for each level of difficulty for the Grid, Addition, FDS and BDS, and Trails tasks are presented in **Fig. 3**. Although EEG-engagement levels changed across the levels of the tasks, the relationships were not linearly related to the task difficulty levels as demonstrated for the EEG-workload measures. Bi-variate correlations between EEG-workload and objective and subjective measures for the FDS and BDS are illustrated in the box plots in **Figs. 4a and b**, respectively. The median correlation between EEG-workload and the objective was −0.68 with a range of −0.90 to 0.02 for the FDS and −0.71 with

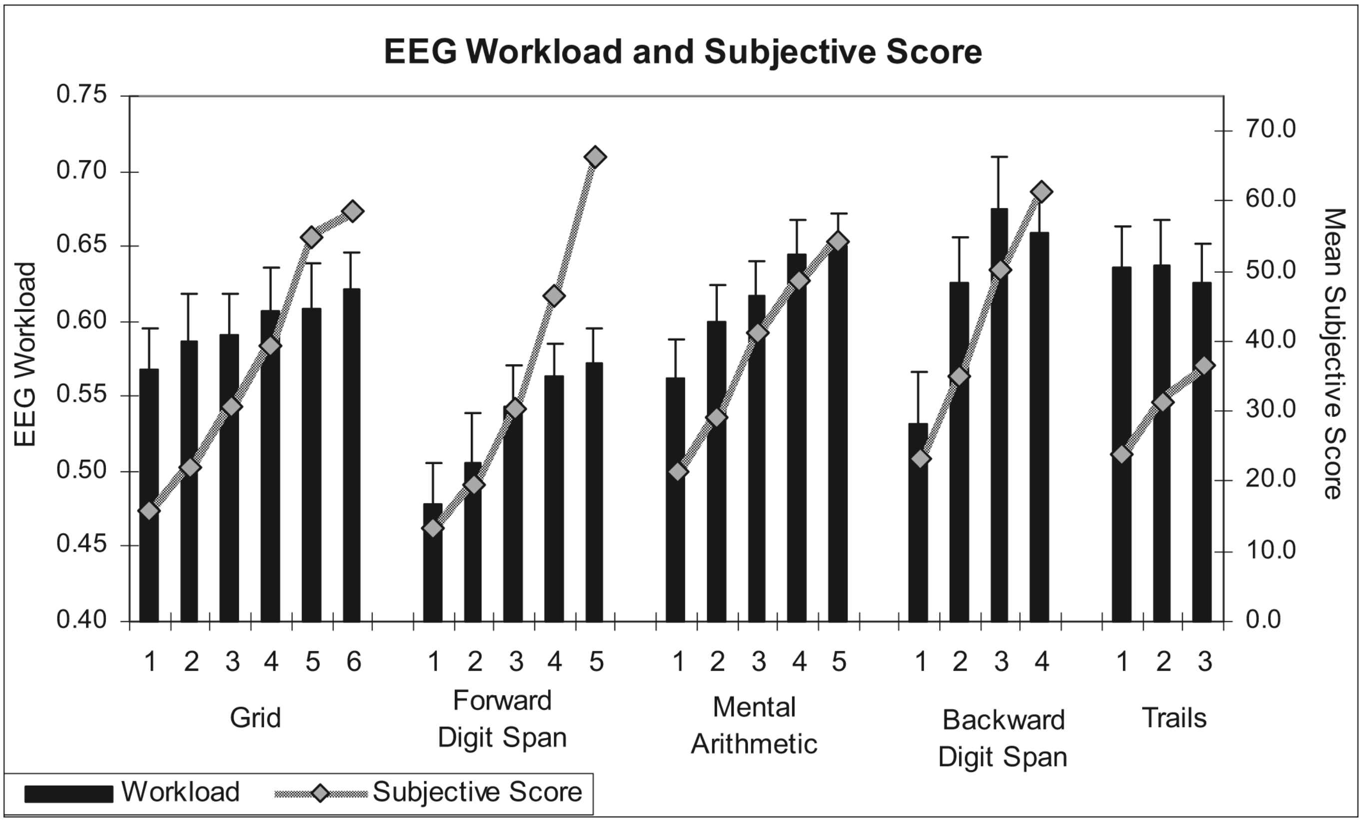


Fig. 1. Mean ± SEM. EEG-workload and mean subjective rating scores for each difficulty level of the grid, forward digit span, mental arithmetic, backward digit span, and trails tests for the model development group (n = 13).

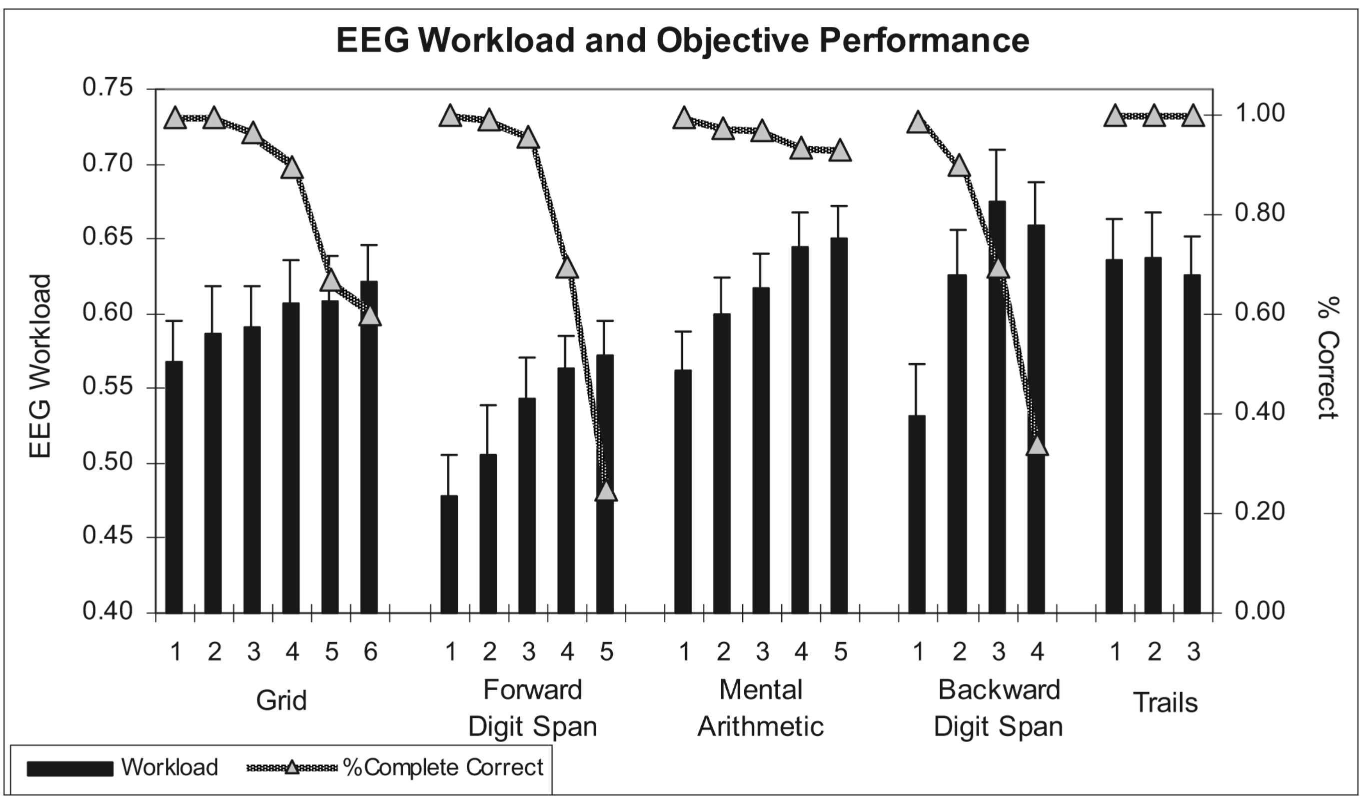


Fig. 2. Mean ± SEM. EEG-workload and mean objective performance scores for each difficulty level of the grid, forward digit span, mental arithmetic, backward digit span, and trails tests for the model development group (n = 13).

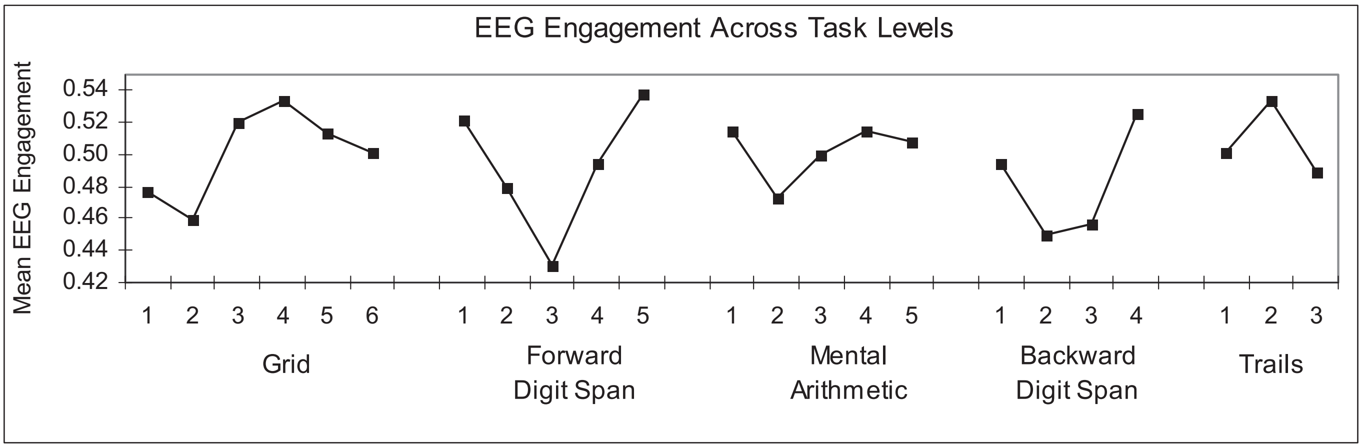


Fig. 3. Mean EEG-engagement for each difficulty level of the grid, forward digit span, mental arithmetic, backward digit span, and trails tests for the model development group (n = 13).

a range of −0.96 to −0.17 for the BDS; for the subjective, the median was 0.79 with a range of −0.47 to 0.90 for the FDS and 0.80 with a range of 0.67 to 1.0 for the BDS.

Different patterns of relationships between the measures were observed across participants. Because the measures reveal different aspects of the "ground truth" with respect to workload levels, canonical correlations were employed (CANCORR macro in SPSS, Release 8.0) to calculate a single aggregate measure of association in the model development data set between the EEG-workload and subjective and objective measures. As opposed to multiple bi-variate correlations, canonical correlations are linear functions that maximize the relationship between the two sets of variables. For the Lockheed Martin data, canonical correlations were calculated for each individual across the 23 tasks/levels (**Fig. 4c**) comparing the EEG-workload variable sets (%classified high workload and probability of high workload) to the objective and subjective variable sets (%complete correct, %partial correct, assigned level of difficulty, and subjective perception of difficulty). The canonical correlation had a median of 0.82 with a range of 0.63 to 0.92.

Although as a multivariate test, sample size recommendations generally specify a larger number of observations than tested here, canonical correlations were utilized in this circumstance less as an inferential test and more as a metric of association. As outliers can have a large impact on the calculations, all cases were examined for extreme values using Mahalanobis distance. There were no outliers noted. The box plots in Fig. 4 illustrate the results of the bivariate and Canonical correlations for this initial data set. Chi-square tests were significant for the canonical correlations for 9 of the 13 participants.

Cross-validation of the EEG-mental workload measure was completed with a new group of 17 participants evaluated at ABM using the FDS and BDS tests. The ABM versions of the digit span tasks were modified to limit the amount of time to respond. Two difficulty levels were added to the BDS, because prior work suggested that some participants became frustrated and "gave up" at some point in the BDS and there was significant variability in when this occurred. The additional levels provided a full spectrum of EEG for all participants prior to and after giving up on the task.

Fig. 5 presents the mean workload levels as classified by the EEG model for each level of difficulty for the FDS and BDS tasks with the associated mean objective performance and subjective ratings (Fig. 5a and b, respectively) for each level of each task. These data provide confirmation of the validity of the EEG measure across participants for the forward and backward digit span tests. Canonical correlations with a median of 0.66 and a range of 0.30 to 0.91 were also calculated for each individual for the probability of high workload on the FDS and BDS and the subjective and objective performance measures (**Fig. 6**). The mean EEG-engagement values for each level of the digit span for the cross-validation group are presented in **Fig. 7**. These data suggest changes in engagement that are not linearly related to task difficulty in the FDS and BDS and that a more complex relationship may exist between the EEG-engagement index and the task levels.

Evaluation of the EEG engagement and workload measures was also conducted during the 3C-VT (**Fig. 8**). Mean reaction times, EEG-engagement and EEG-workload levels were calculated for each of the 5-min quarters of the 20-min test. Repeated measures ANOVA was performed across the four quarters. Probability values reported are based on the Greenhouse-Geisser corrected degrees of freedom. As expected, repeated measures ANOVA revealed significant effects over time with reaction time increasing [$F(1,64) = 104.92$, $p < 0.001$] and engagement decreasing [$F(1,64) = 216.08$, $p < 0.001$]. However, the workload levels did not show a significant linear increase over the 20-min test. Effect sizes were large for reaction time (Cohen's SD = 1.11) and EEG-engagement (Cohen's SD = 2.83).

These data confirm previous reports by the investigators that during the 20-min test, participants show increasing reaction time and a corresponding decrease in the EEG-engagement level. This effect becomes increasingly evident as a function of sleep deprivation, fatigue, or withdrawal from stimulant drugs such as nicotine (7,29,53). The fact that the mental workload index did not change over time was expected in the

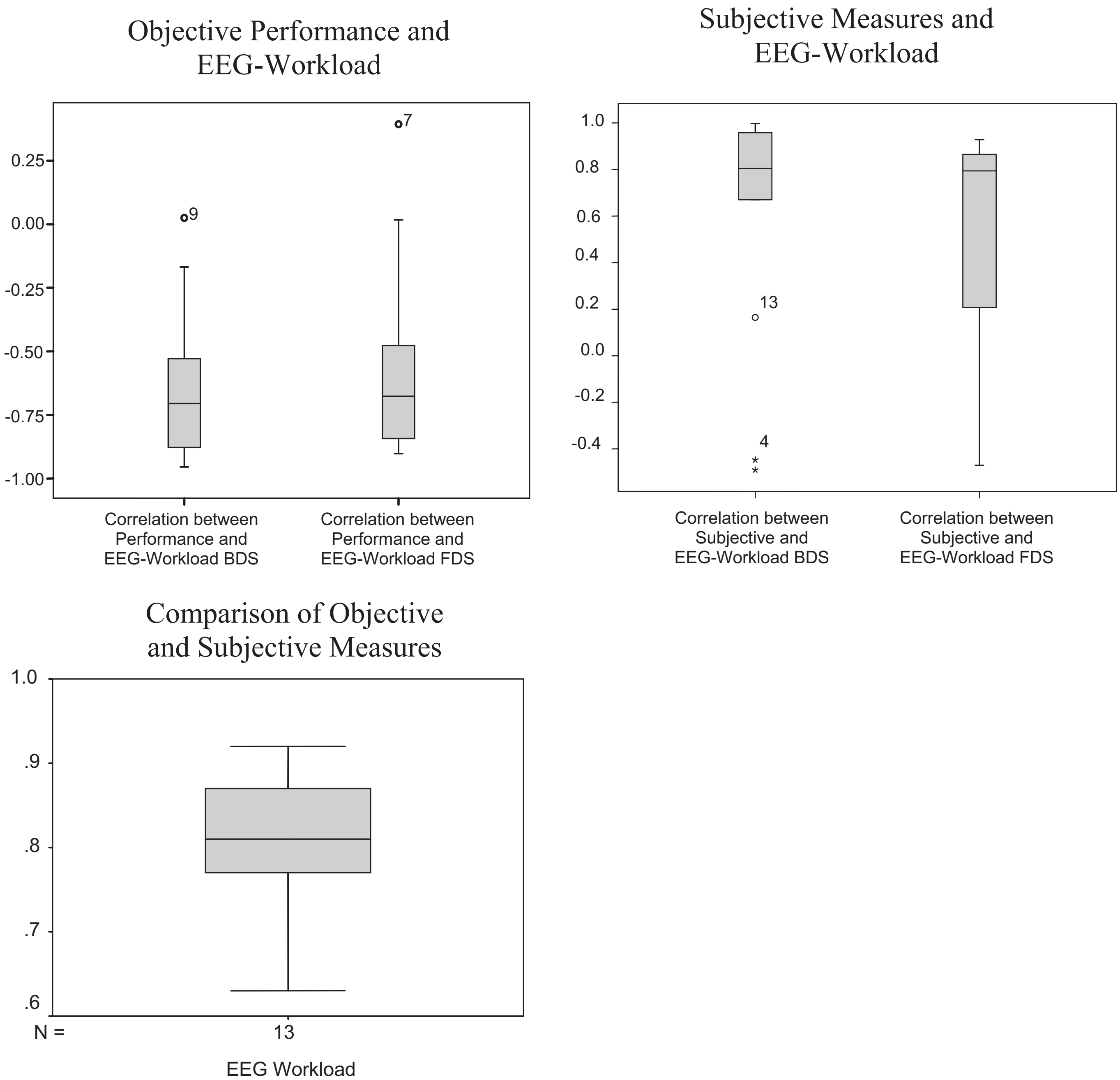


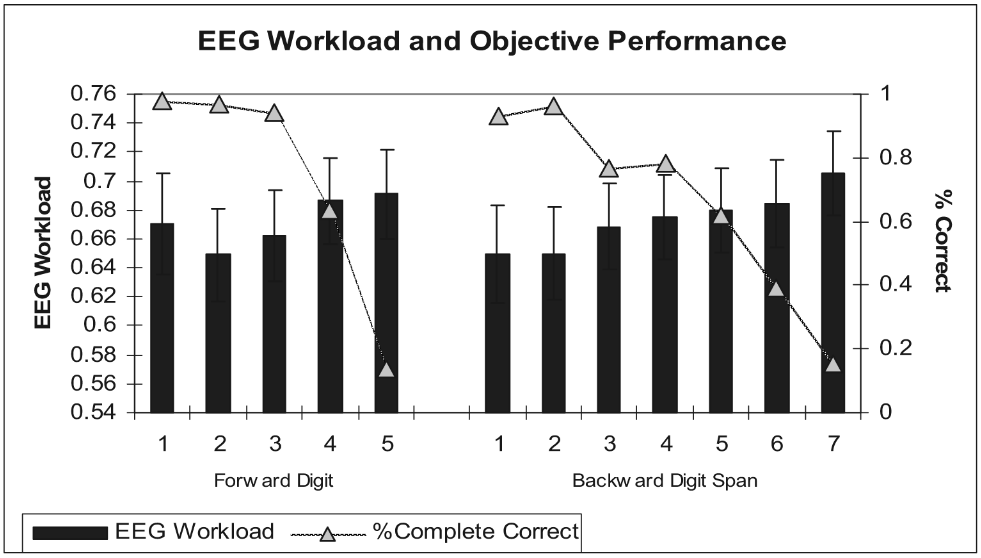
Fig. 4. Bi-variate correlations for individual participants (n = 13) comparing EEG-workload with a) objective, b) subjective measures, and c) canonical correlations with both objective and subjective measures. The box plots display the median of the correlations, with ~50% of the data represented by the shaded area (fourth-spread), and ~99% of the data within horizontal bars (outlier cutoff points).

3C-VT, a task with minimal demands on working memory or complex cognitive processing.

For the learning and memory tests, mean EEG-engagement and workload were computed for each of the encoding and recognition periods of three types of learning and memory tests (standard, interference, and verbal). For EEG-engagement, repeated measures ANOVA indicated a significant effect for task type [$F(1, 49) = 13.65$, $p < 0.001$] and encoding/recognition [$F(1, 49) = 15.176$, $p < 0.001$] (**Fig. 9**). For EEG-engagement, the interference was significantly different from both standard [$F(1, 49) = 22.39$, $p < 0.001$] and the verbal [$F(1, 49) = 11.05$, $p < 0.001$], while verbal was also significantly different from standard [$F(1, 49) = 4.73$, $p < 0.05$].

The task type effect relates to the level of task difficulty. Confirmation of the task difficulty differences was observed in the significant main effect for task type [$F(1, 49) = 44.56$, $p < 0.001$] for percentage correct performance (**Fig. 10**). This increase in task difficulty is also reflected in the increase in EEG-engagement (Fig. 9).

The EEG-workload measures were also significantly increased during the encoding period of all memory tests when compared with the recognition period (**Fig. 11**). However, only the encoding/recognition effect for



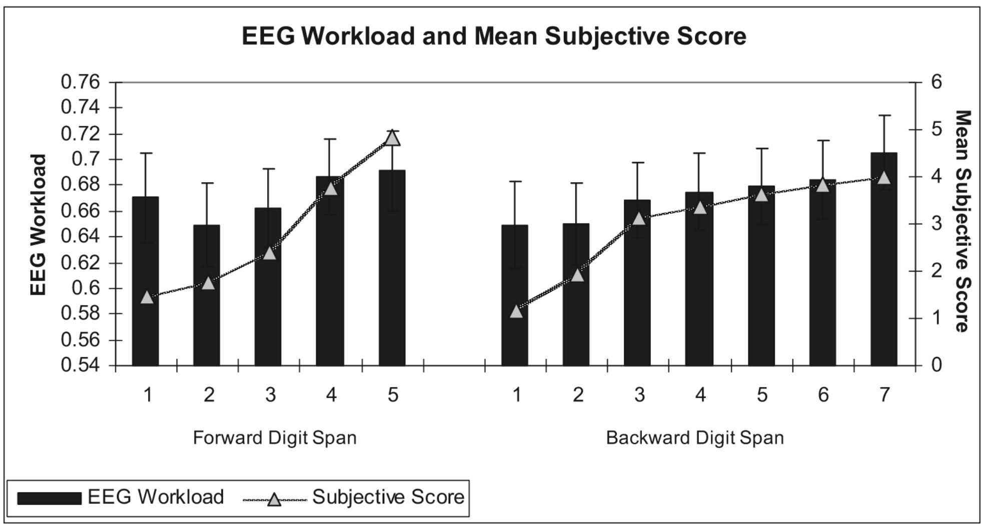


Fig. 5. Mean ± SEM. EEG-workload and a) objective performance scores and b) subjective rating scores for each difficulty level of the forward digit span and backward digit span for the cross validation group (n = 17).

EEG-mental workload was significant [$F(1, 49) = 34.79$, $p < 0.001$]. These data suggest that the EEG reflects an increased allocation of attentional resources and mental workload during the encoding period.

To summarize, EEG-workload but not engagement increased linearly across the multiple levels of forward/backward-digit-span, grid-recall, and mental-addition tests. EEG-engagement but not EEG-workload decreased as a function of time-on-task during the 20-min 3C-VT and for the learning and memory tests, EEG-engagement, and mental workload were higher during the encoding period than the recognition period and increased as a function of task difficulty. EEG measures were significantly correlated with both subjective and objective performance metrics.

DISCUSSION

These data suggest that the EEG can provide an unobtrusive method for monitoring dynamic fluctuations in cognitive states including task engagement and mental workload. The temporal resolution of the EEG allows for precision calculations for each 1 s or 0.5 s of data; however, the detectable states are global in nature and the validation and interpretation of changes in cognitive state on a second-by-second basis require further investigation.

The results of these studies in combination with prior work (2-9,37,48) indicate that the EEG engagement index is related to processes involving information-gathering, visual scanning, and sustained attention. The EEG-workload index increases with working memory load and with increasing difficulty level mental arithmetic and other problem-solving tasks. The two metrics were shown to operate concordantly or independently, depending on the task environment, the level of task demands, and the amount of effort required by the individual to complete the task. In the present study, a combination of multi-level task design, objective per-

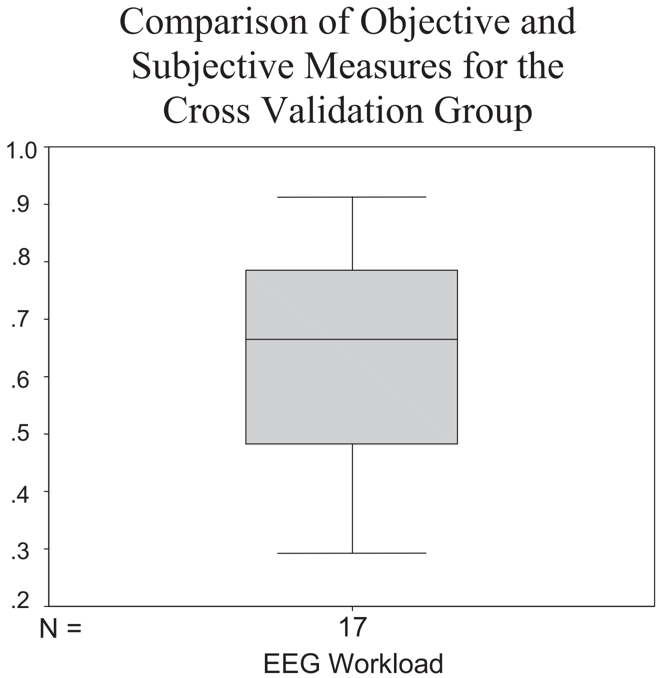


Fig. 6. Canonical correlations between EEG-workload and objective performance and subjective rating scores for each difficulty level of the forward digit span and backward digit span for the cross validation group (n = 17). The box plot displays the median of the correlations, with ~50% of the data represented by the shaded area (fourth-spread), and ~99% of the data within horizontal bars (outlier cutoff points).

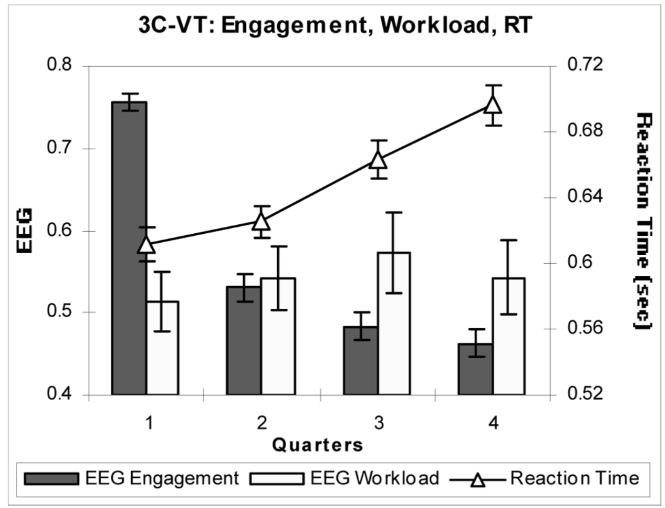


Fig. 8. Mean ± SEM. EEG-engagement, EEG-workload, and reaction time for each 5-min quarter of the 3-Choice Vigilance Test (n = 65 for EEG-engagement and reaction time, n = 27 for EEG-workload).

formance metrics such as reaction time, and percentage of correct responses and subjective ratings to assess the perceived level of effort were used to validate the EEG metrics.

Specifically, the EEG measures dissociated during a sustained vigilance task with a minimal load on working memory. Reaction time increased and EEG-engagement decreased over the 20-min vigilance session while workload remained constant.

During multi-level mental addition, grid location, and forward and backward digit span tests, the EEG-workload increased linearly as a function of increasing task difficulty. During these same multi-level tasks, EEG-engagement showed a pattern of change that was variable across tasks, levels, and participants. The pattern included a relatively high engagement during the first level of each task and a decrease in engagement for the second level of task difficulty, suggesting an initial task adaptation or novelty response. In this study, the first level of each task was always the easiest and the difficulty level was incrementally increased with each level. In future studies, however, a random mix of difficulty levels could be used to eliminate the novelty effects on the EEG. Because participants were provided as much time as needed to complete the trails task, EEG engagement and workload and performance were constant across the three difficulty levels.

In a series of image and verbal learning and memory tests designed to be increasingly difficult, both EEG-engagement and EEG-workload were higher during the encoding period than the recognition period and increased as a function of task difficulty. The level of EEG engagement and workload during encoding was positively related to the level of performance on each of the learning and memory tests.

The conventional analysis of the EEG involving computation of the mean power spectral densities within the classically defined frequency bands including alpha, beta, theta, delta, and gamma has been reported as the foundation for several EEG-based models of mental workload (17-19,44-47). The modeling technique described in this paper incorporates multiple EEG variables across scalp sites and 1-Hz frequency bins (from 1 Hz – 40 Hz) to be used as inputs to quadratic and linear discriminant function analyses that provide classifications for each second of EEG. Models are constructed using stepwise multiple regression analyses to select

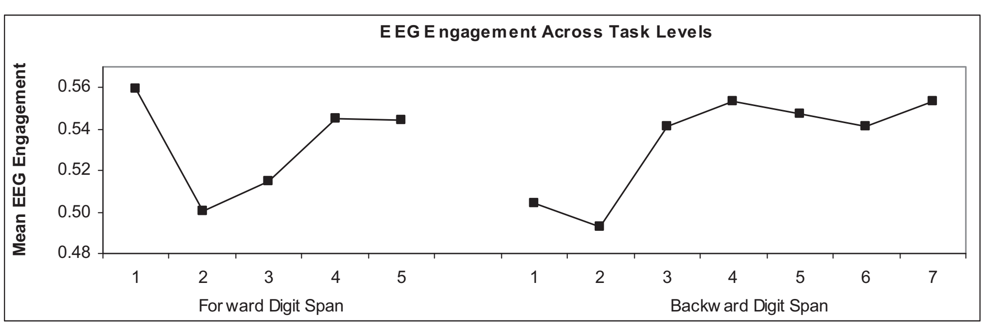


Fig. 7. Mean EEG-engagement for each difficulty level of the forward digit span and backward digit span for the cross validation group (n = 17).

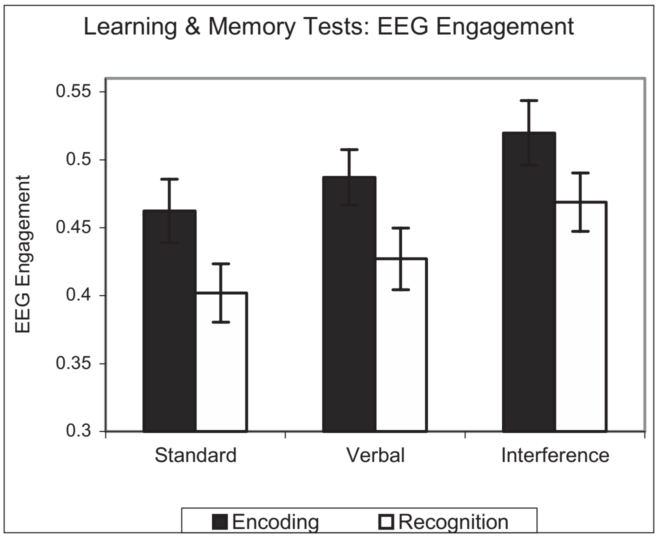


Fig. 9. Mean ± SEM. EEG-engagement during the encoding and recognition/recall periods for the standard, verbal, and interference learning and memory tests (n = 50).

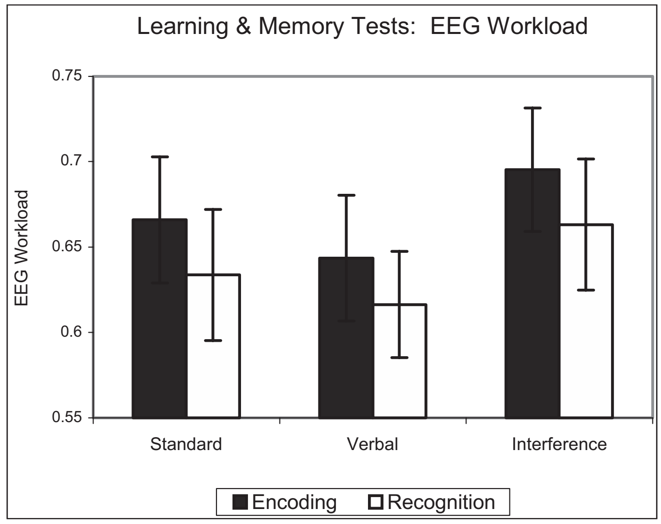


Fig. 11. Mean ± SEM. EEG-workload during the encoding and recognition/recall periods for the standard, verbal, and interference learning and memory tests (n = 15).

those EEG variables that optimize the identification and classification of cognitive states within specified task environments. For the engagement index, simple baseline tasks are used to fit the classification model to the individual.

These methods have proven valid in EEG quantification of drowsiness-alertness during driving simulation, simple and complex cognitive tasks, and in military, industrial, and educational simulation environments (2-6,23-25,33,48,50), quantifying mental workload in military simulation environments (2,4,33,37,50), distinguishing spatial and verbal processing in simple and complex tasks (3), characterizing alertness and memory deficits in patients with obstructive sleep apnea (7,53), and identifying individual differences in susceptibility to the effects of sleep deprivation (5). The EEG-workload measure was recently proven valid when compared with an objectively derived analysis of total workload and visual load score (37).

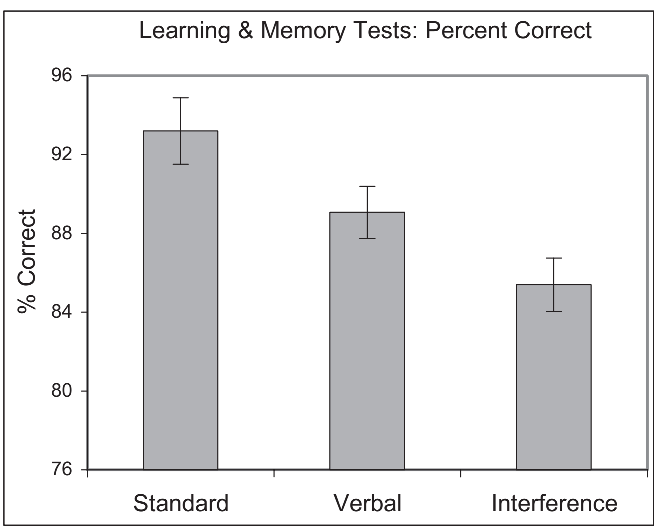


Fig. 10. Mean ± SEM percentage correct responses for the standard, verbal, and interference learning and memory tests (n = 50).

The approach described in this paper allows a complex mathematical model to be created using multiple EEG variables across frequencies and scalp locations. Table I lists the number, sensor locations, and frequency bins of the model-selected variables used to classify workload and engagement. The engagement index relies heavily on EEG variables from the frequency bins in the beta and gamma bands, but also includes variables from delta, theta, and alpha frequencies (Table I). The workload measure also includes multiple variables from all of the frequency ranges.

In contrast, previous models of engagement and workload developed by the Old Dominion/NASA Langley group and Gevins and Smith employ conventional alpha, beta, and theta EEG bands (17-19,38,44). Smith and Gevins (44) recently reported a refinement of their EEG workload model that included quantification of alpha and theta band activity recorded from the frontal executive, central sensorimotor, and posterior visual systems postulated to be linked to the regional cortical activation associated with decision-making, motor control, and visuoperceptual demands, respectively (19). All regional indices increased linearly during performance of low, medium, and high load versions of a flight simulator task and correlated with subjective reports of perceived mental workload.

The value of using the established frequency band analyses is that they can be linked historically to methods applied and reported in EEG research and interpretation over the past 50 yr. The risk in using simple metrics such as an increase in midline theta with a decrease in mean alpha or ratios of alpha, theta, and beta is an oversimplification of cognitive state assessment. For example, Gevins and Smith repeated their flight simulator experiment after sleep depriving participants and reported that the subjective mental effort was negatively correlated with frontal activation after sleep deprivation in contrast to the positive correlation between frontal activation and subjective mental effort in the fully rested condition (19,44). They interpret these data as "problematic" for the development of auto-

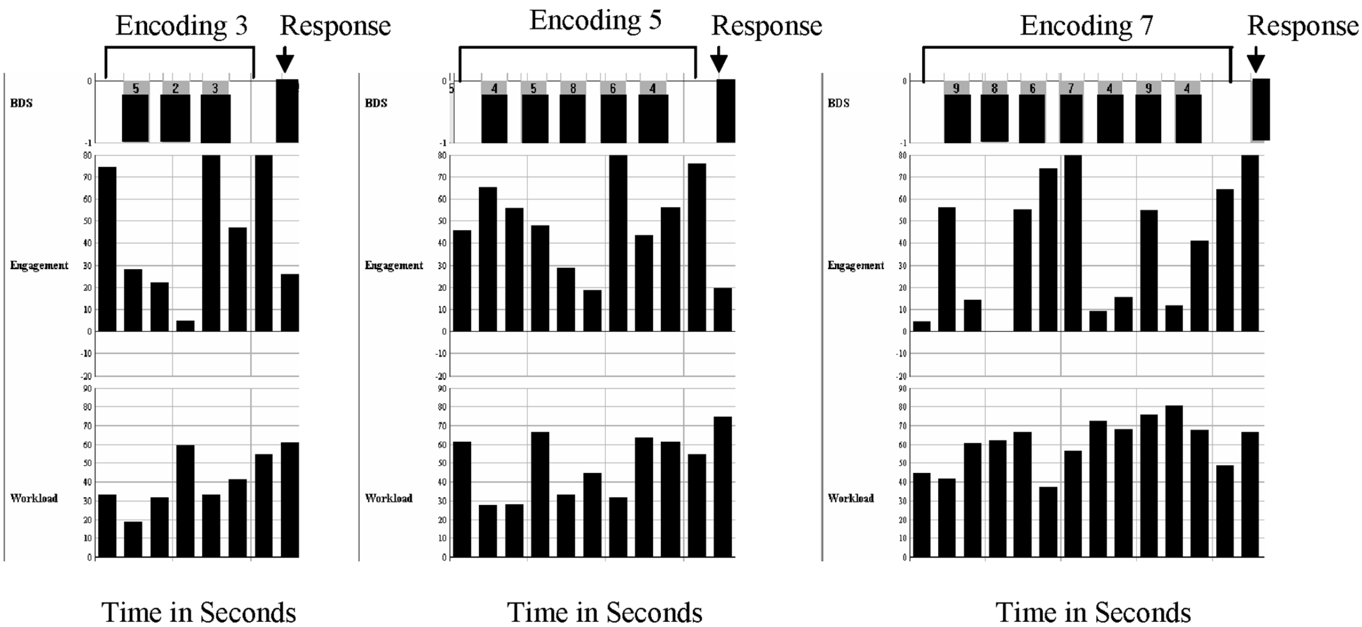


Fig. 12. Comparison of 1-s levels of EEG-engagement and EEG-workload during the backward digit span. The top row, Backward Digit Span (BDS) row, identifies the presentation of a series of 3, 5, or 7 digits designated as the "encoding" period, followed by the response. The second row illustrates the engagement index with one histogram bar for each 1-s quantification of the EEG-engagement level. The third row illustrates the workload index with one histogram bar for each 1-s quantification of the EEG-workload level.

mated systems that use brain activation in a closed-loop system designed to identify when operators are overloaded or underloaded and trigger greater information dissemination or task re-allocation.

The model presented in this paper has the potential for avoiding the type of misclassifications reported in the Gevins and Smith experiment (19,44) by combining a workload classifier, an engagement classifier, and a drowsiness classifier (presented in previous work; see references 2 and 3) that are derived from a DFA (trained with data from over 100 sleep-deprived participants) that included variables that are sensitive to sleep deprivation. The use of multiple classifiers derived from a complex combination of EEG variables facilitates highly sensitive and specific classifications of cognitive state changes.

Inspection of the data on a second-by-second timescale (**Fig. 12**) suggests the possibility that associations between EEG workload and engagement levels can be identified when aligned with specific time-locked task events. In the backward digit span example provided in Fig. 12, the engagement levels are high during digit encoding and during the response period. The workload levels increase with increasing number of digits to be encoded. In-depth analyses using time series analysis are planned to further assess the relationships between EEG and stimulus characteristics (e.g., easy/difficult) and response parameters (e.g., correct/incorrect responses).

The workload and engagement classifiers have been integrated into real-time, closed-loop automated computing systems to implement dynamic regulation and optimization of performance during a driving simulation task and in the Aegis C2 and Tactical Tomahawk Weapons simulation environments (3,4,6,50). The EEG-classifiers are also being used for industrial and military ergonomic assessments and as part of an interactive learning environment for high school and college science students (37,48).

Future applications of the EEG classifiers presented in this paper include evaluating the effects of HCI, human factors, and ergonomic design on cognitive state to provide an objective method for guiding the development and testing of new interfaces. These EEG metrics may also be useful in assessing the effectiveness of training and simulation programs or in the acquisition of synchronized data from multiple individuals to provide unique characterizations of group dynamics. Although the EEG provides a rich potential data source for cognitive state analysis, additional physiological parameters such as heart rate variability, fNIR, and eye-tracking may be required to extend the capabilities to include quantification of stress and emotional states.

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