Use of EEG Workload Indices for Diagnostic Monitoring of Vigilance Decrement

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Objective: A study was run to test which of five electroencephalographic (EEG) indices was most diagnostic of loss of vigilance at two levels of workload.

Background: EEG indices of alertness include conventional spectral power measures as well as indices combining measures from multiple frequency bands, such as the Task Load Index (TLI) and the Engagement Index (EI). However, it is unclear which indices are optimal for early detection of loss of vigilance.

Method: Ninety-two participants were assigned to one of two experimental conditions, cued (lower workload) and uncued (higher workload), and then performed a 40-min visual vigilance task. Performance on this task is believed to be limited by attentional resource availability. EEG was recorded continuously. Performance, subjective state, and workload were also assessed.

Results: The task showed a vigilance decrement in performance; cuing improved performance and reduced subjective workload. Lower-frequency alpha (8 to 10.9 Hz) and TLI were most sensitive to the task parameters. The magnitude of temporal change was larger for lower-frequency alpha. Surprisingly, higher TLI was associated with superior performance. Frontal theta and EI were influenced by task workload only in the final period of work. Correlational data also suggested that the indices are distinct from one another.

Conclusions: Lower-frequency alpha appears to be the optimal index for monitoring vigilance on the task used here, but further work is needed to test how diagnosticity of EEG indices varies with task demands.

Application: Lower-frequency alpha may be used to diagnose loss of operator alertness on tasks requiring vigilance.

Keywords: attentional processes, vigilance (sustained attention), monitoring, supervisory control, mental workload

INTRODUCTION

Vigilance has become increasingly salient as a critical human factors issue because of the increasing automation of technology (Warm, Parasuraman, & Matthews, 2008). In the applied setting, vigilance decrement refers to loss of detection of critical stimuli during a prolonged, continuous work shift. Vigilance decrement has been observed in a variety of industrial, transportation, security, and medical settings (see Parasuraman, 1986, and Warm et al., 2008, for reviews). In laboratory studies, vigilance decrement is commonly observed within the first 20 to 30 min of performance (Molloy & Parasuraman, 1996) and, on some tasks, over even shorter durations (Gillberg & Åkerstedt, 1998; Teichner, 1974; Temple et al., 2000). The time course of vigilance decrement in applied settings varies depending on task characteristics (Craig, 1984; See, Howe, Warm, & Dember, 1995), but loss of vigilance over durations of less than 1 hr has been observed in contexts as diverse as vehicle driving (Verster & Roth, 2012) and student attention to lectures (Young, Robinson, & Alberts, 2009). Operators monitoring automated technology may be especially vulnerable to such performance decrements. Detection failures may have severe consequences, given that automation has been introduced into safety-critical domains, such as vehicle operation (Young & Stanton, 2007), air traffic control (Langan-Fox, Sankey, & Canty, 2009), and military intelligence, surveillance, and reconnaissance (Swanson et al., 2012). Molloy and Parasuraman (1996) demonstrated a vigilance decrement in the operator’s ability to detect even a single automation failure across a 30-min timespan.

Difficulties in sustaining attention are difficult to counter through design or training solutions (Davies & Parasuraman, 1982). Hence,
human factors solutions may require “monitoring the monitor” (Wiener, 1973) in order to detect loss of vigilance prior to the operator’s committing a critical error. Wiener (1973) originally suggested using loss of performance as an input for driving task characteristics adaptively. However, in many vigilance settings, critical signals may be infrequent, and so continuous psychophysiological monitoring may be more effective in detecting loss of alertness. Monitoring should preferably be diagnostic in identifying the source of attentional impairment, such as loss of resources or disinclination to exert effort on the task (Matthews, Warm, Reinerman, Langheim, Washburn, et al., 2010). Electroencephalographic (EEG) indices of vigilance have been studied most often in studies of adaptive automation (Parasuraman & Wilson, 2008). Authors of these studies aim to identify EEG indices that may be used to trigger technological support to maintain performance (Freeman, Mikulka, Scerbo, & Scott, 2004). Several distinct indices have been suggested (Fairclough, 2009). The objective for the present study was to compare several prominent EEG indices of alertness and workload as concomitants of the vigilance decrement in performance.

(There is some scope for terminological confusion. We use sustained attention as a broad requirement for a range of tasks that require attention to be maintained over extended durations. Vigilance refers more specifically to sustaining attention to displays or to discrete sources of stimuli in other sensory modalities. Thus, prolonged performance on a psychomotor tracking task would be better described as requiring sustained attention rather than vigilance. Alertness refers to an attribute of neurocognitive functioning that supports vigilance. Other functions, such as compensatory effort, may also contribute to vigilance.)

**EEG Indices of Alertness and Effort**

There are two complementary perspectives on using EEG for continuous monitoring of the operator’s fitness to maintain vigilance. Traditionally, vigilance decrement was attributed to loss of cortical arousal resulting from the monotony of the task, a hypothesis supported by the effects of arousing and de-arousing agents on vigilance (Davies & Parasuraman, 1982; Matthews, Davies, Westerman, & Stammers, 2000). More recent studies showed that although monotony and loss of arousal may contribute to vigilance decrement (Scerbo, 2001), performance also fails because of prolonged cognitive overload (See et al., 1995). According to the resource theory of vigilance decrement (Davies & Parasuraman, 1982; Warm et al., 2008; Warm, Dember, & Hancock, 1996), prolonged mental work leads to depletion of attentional resources required for signal detection. A meta-analysis of factors influencing the vigilance decrement suggests that resource theory is valid across a range of task parameters, including duration, stimulus presentation time, and event rate (See et al., 1995). Warm et al. (1996) used the NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988) to confirm that mental workload increased during the period of the vigil, consistent with resource theory. The theory can be reconciled with arousal theory to the extent that one component of arousal, energetic arousal, may enhance the functioning of frontal areas that support attentional resources, via midbrain dopaminergic afferents to prefrontal cortex (Matthews, Warm, Reinerman, Langheim, Washburn, et al., 2010).

Resource theory suggests that psychophysiological monitoring for increased workload, in the absence of any change in task demand, might be used to detect incipient loss of vigilance. This strategy is supported by recent research using Transcranial Doppler sonography to measure cerebral blood flow velocity (CBFV; Warm, Tripp, Matthews, & Helton, 2012). Declines in CBFV tend to parallel the temporal performance decrement and appear to be controlled by the same workload factors (Matthews, Warm, Reinerman, Langheim, & Saxby, 2010; Shaw, Satterfield, Ramirez, & Finomore, 2013). Right-hemisphere CBFV is especially diagnostic, consistent with brain-imaging data suggesting that vigilance is controlled by right-hemisphere circuits (Langner & Eickhoff, 2012), although there is some variation in lateralization with task demands (Shaw et al., 2013).

EEG research has followed both arousal and resource theory perspectives on vigilance in deriving potential diagnostic indices (Fairclough
Early EEG studies showed increases in alpha power, and also increases in theta, during the vigil, indicative of loss of cortical arousal (Davies & Parasuraman, 1982; O’Hanlon & Beatty, 1977). Alpha has subsequently proved to be diagnostic of cognitive fatigue and loss of alertness in a range of applied settings (Borghini et al., 2012; Craig & Tran, 2012). There have been two noteworthy further developments. Klimesch (1999) proposed splitting alpha into upper- and lower-frequency bands. Upper alpha (alpha-2) is suppressed by information-processing requiring semantic memory, whereas lower alpha (alpha-1) reflects the traditional notion of alpha suppression as an index of alertness. Distinguishing these two bands might improve the diagnosticity of alpha for loss of vigilance. Also, Pope, Bogart, and Bartolome (1995) pointed out that multiple EEG bandwidths may be indicative of alertness. They defined an Engagement Index (EI; Freeman et al., 2004; Pope et al., 1995) as beta / (alpha + theta). EI is useful for monitoring alertness during vigilance (Mikulka, Scerbo, & Freeman, 2002) and continuous tracking (Freeman, Mikulka, Prinzel, & Scerbo, 1999) tasks. EI also has potential as a brain state measure that may be used to drive adaptive automation (Freeman et al., 2004). However, EI may reflect general alertness rather than commitment of effort to the task (Zhang, Peng, Liu, Raisch, & Wang, 2013).

The resource theory of vigilance (Warm et al., 1996, 2008) implies that whereas arousal may influence resource availability, allocation of resources to processing (mental effort) may be more proximally related to vigilance, so that measures of changes in effort are diagnostic (Smit, Eling, Hopman, & Coenen, 2005). In hemodynamic studies, frontal blood oxygenation measured using near-infrared spectroscopy increases over time (De Joux, Russell, & Helton, 2013). Thus, primary loss of resources (indexed by CBFV) may be distinguished from the increase in effort (indexed by oxygenation) that represents the compensatory response (Funke et al., 2010). Frontal theta power typically increases with mental workload and demands on working memory (Borghini et al., 2012; Gevins & Smith, 2003), suggesting it, too, is sensitive to mental effort. Frontal theta also increases during vigilance (Paus et al., 1997) and may reflect increases in mental effort associated with failing vigilance (Smit et al., 2005). Again, the index may be enhanced by combining information from multiple bands. In several studies using multicomponent tasks, Gevins and his colleagues (e.g., Gevins & Smith, 2003; Smith, Gevins, Brown, Karnik, & Du, 2001) observed that workload manipulations increased theta power at anterior frontal and frontal midline sites and decreased alpha at parietal sites. Their task load index (TLI) is the ratio of frontal midline theta to parietal alpha.

It is unclear which of the various indices is optimal for diagnostic monitoring. Hockey et al. (2009) varied workload on a cyclic basis using a simulated process control task, and compared EI, TLI, and cardiac response. TLI was more consistently related to control demands than was EI. TLI was identified with the “strain” experienced by participants as they attempted to compensate for potential overload. Fairclough and Venables (2004) found that increasing workload on a multicomponent cognitive task produced a pattern of theta augmentation together with alpha suppression, implying that the TLI would have been sensitive to workload, whereas Freeman et al.’s (2004) EI index was insensitive to workload. However, comparative evaluations of the EEG indices described here have not been performed for vigilance tasks.

**Study Aims**

Our aim was to compare the validity of the various EEG indices listed in Table 1 as indicators of vulnerability to vigilance decrement. We used a sensory vigilance task that requires participants to detect briefly presented critical signals in a display resembling an air traffic control display (Hitchcock et al., 2003). The intent was not to simulate air traffic control but to investigate EEG concomitants of vigilance decrement on a resource-limited task. The task shows a reliable vigilance decrement in performance, and it elicits the decreases in subjective task engagement and CBFV response characteristic of high-workload vigilance tasks (Hitchcock et al., 2003; Matthews, Warm, Reinerman, Langheim, Washburn, et al., 2010). The task also affords manipulation
of task load. Hitchcock et al. (2003) showed that providing a cue that a critical signal (target) was imminent reduced vigilance decrement and mitigated loss of subjective task engagement. Furthermore, cue effects on performance were mirrored by changes in right-hemisphere CBFV. Cuing allows participants to conserve their resources, reducing resource depletion and consequent performance decrement.

We aimed to test how the cuing manipulation and time on task influenced the various EEG workload metrics to determine which metric was optimal for monitoring for loss of vigilance. Loss of alertness is signaled by higher alpha-1 power (Klimesch, 1999) and lower EI (Freeman et al., 2004). It was predicted that alpha-1 would increase and EI would decrease over time, especially in the uncued condition. Conversely, the two mental effort indices, frontal theta and TLI (Gevins & Smith, 2003), should increase with time on task. Again, sensitivity to time on task should be greater in the uncued condition because it requires a greater allocation of resources. We also computed correlations between the various indices to test their convergence and divergence; previous studies have generally used sample sizes insufficient to secure reliable estimates of correlations.

<table>
<thead>
<tr>
<th>TABLE 1: Summary of Electroencephalographic Indices Used in Study</th>
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<tr>
<td>Index</td>
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<td>------------------------</td>
</tr>
<tr>
<td>Alpha-1 (suppression)</td>
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<tr>
<td>Alpha-2 (suppression)</td>
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<tr>
<td>Engagement Index (EI)</td>
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<tr>
<td>Frontal theta</td>
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<td>Task Load Index (TLI)</td>
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Participants were allocated at random to the no-cue condition and 46 to the cue condition. Participants were required to be free of psychiatric and medical disorders at the time of the study. All were right-handed (as determined by interview), with normal or corrected-to-normal vision, and were native Russian speakers.

**Materials and Apparatus**

**Vigilance task.** Participants were individually tested in a small, artificially lit laboratory room, isolated from noise and electromagnetic radiation. They were seated at a computer workstation so as to view a screen from a distance of approximately 70 cm. They performed a slightly modified version of the Hitchcock et al. (2003) task, programmed with SuperLab 2.0 software. On-screen instructions were in Russian. Participants monitored a display that was described to participants as an air traffic control display. It consisted of a “city” bounded by a thin white border and ringed by three circular white “outer markers” and two “aircraft” represented by two light gray lines, presented on a darker gray background. The aircraft were equidistant from the city and approached it from opposite headings, either from northwest to southeast or from northeast to southwest. The critical target stimuli for detection were cases in which the two aircraft were aligned on a potential collision course over the center of the city. Nontarget stimuli were those in which flight paths were displaced so that the aircraft would not collide (see Figure 1). Stimulus dimensions were the same as those of Hitchcock et al. (2003).
Task duration was 40 min. There were 400 stimuli presented in each 10-min block of trials, of which 380 were nontarget stimuli, 10 were target stimuli, and 10 were the cue word LOOK (in Russian). Thus, in relation to the air traffic control displays, the event rate was 39 events per minute. Ten of the events were critical signals for detection, and signal probability was .026. In the uncued condition, participants were instructed to ignore the cue word. In the cued condition, participants were told that a target would probably follow the cue in the next 5 stimuli. In fact, this was true for 9 of 10 cue presentations. One additional target was not preceded by the cue word. In the uncued condition, occurrence of the cue word was uninformative about the occurrence of the target. Each stimulus was presented for 80 ms, followed by a blank screen. Participants were instructed to click a mouse if they detected a target. Responses to targets were recorded as correct detections if they arrived within 1,700 ms of stimulus onset. Responses that followed nontargets were recorded as false positives. In a practice version of the task, correct detections, missed targets, and false positives were followed by spoken feedback, that is, the Russian words for correct, missed, and incorrect, respectively. No feedback was given in the main task.

**Questionnaires.** All questionnaires were translated into Russian. The Dundee Stress State Questionnaire (DSSQ; Matthews et al., 2002; Matthews, Szalma, Panganiban, Neubauer, & Warm, 2013) was used to measure subjective state. The DSSQ measures 11 first-order dimensions of subjective state expressed in mood, in task motivation, and in cognitive response. All scales showed adequate Cronbach alphas, ranging from 0.694 to 0.925. The DSSQ is typically scored for three higher-order factors of engagement, distress, and worry (Matthews et al., 2002, 2013). Because the factor analysis that supports...
Higher-order factor score estimation has not been cross-validated in a Russian-speaking sample. We estimated the three higher-order factors as unweighted means of the relevant first-order scales, standardized against the sample mean and standard deviation in pretask data. Engagement was estimated from energetic arousal, intrinsic interest, and concentration scales; distress, from tense arousal, hedonic tone (reverse scored), and confidence (reverse scored); and worry, from self-focus, self-esteem (reverse scored), task-related cognitive interference, and task-irrelevant cognitive interference. These unweighted measures are cruder than factor score estimates but adequate for our purpose of checking whether the task elicited changes in stress state qualitatively similar to those seen in Western samples.

A version of the NASA-TLX (Hart & Staveland, 1988) using modified response scales was embedded in the post-task DSSQ. Participants rated six aspects of workload on 0-to-10 scales: Mental Demand, Temporal Demand, Physical Demand, Performance, Effort, and Frustration. Overall workload was computed as an unweighted mean of the six scales. The modified scale has proved effective in discriminating workload across task manipulations in previous studies (e.g., Matthews et al., 2006).

**EEG**. A Neuron-Spectrum-1 electroencephalograph (Neurosoft Company, Ivanovo, Russia) was used to record EEG data from F1, F2, F3, F4, Fz, C3, C4, Cz, P3, P4, Pz, O1, O2, T3, and T4 sites using Ag-AgCl electrodes, with referent ears electrodes, according to the International 10-20 system. Ear references were linked directly. The ground electrode was placed on the forehead. Signals were sampled at 256 Hz; impedance quality was checked during the experiment and maintained at 5 K ohm throughout data collection. EEG data were recorded continuously during task performance. The EEG data were filtered in the frequency range from 0.05 to 35 Hz. A 50 Hz notch filter was used to reduce main artifacts. Rejection of ocular and movement artifacts was done automatically by the Neuron-Spectrum-1 EEG software, followed by an additional visual inspection for artifacts and manual removal. Approximately 10% of the data were rejected due to artifacts in each participant group.

The arrangement of epochs was performed automatically, following exclusion of artifacts. Each 4-s epoch contained 1,024 signals. The spectral power density (SPD) of the following EEG bands was computed with a fast Fourier transformation applied to each 4-s epoch with Neuron-Spectrum-1 software: theta (4 to 7.9 Hz), alpha-1 (8 to 10.9 Hz), alpha-2 (11 to 13.9 Hz), and beta (14 to 29.9 Hz). Five EEG indices were calculated for each 10-min task period using SPSS software, according to published formulae: (a) and (b) alpha-1 and alpha-2, averaged across all sites recorded (Klimesch, 1999); (c) EI, ratio of beta to (alpha+theta) for central-parietal sites Cz, P3, Pz, and P4 (Pope et al., 1995); (d) frontal theta effort index, averaged across F1, F2, F3, and F4 (Gevins, Smith, McEvoy, & Yu, 1997); and (e) TLI, ratio of theta Fz to alpha Pz (Gevins & Smith, 2003).

**Procedure**

Participants provided written informed consent. Following attachment of electrodes, participants completed a pretest form of the DSSQ. Next, they viewed a demonstration that included all the target and nontarget displays. Then, they practiced the vigilance task for 2 min. Next, a baseline EEG measure was taken with closed and open eyes, lasting 4 min in total. Then, they performed the vigilance task for 40 min, followed by a post-test DSSQ and the NASA-TLX.

**RESULTS**

**Task Performance**

Effects of task parameters on three performance indices—correct detections, false positives, and mean response time (RT) for correct detections—were analyzed using $2 \times 4$ (Cue × Task Period) mixed-model ANOVAs, with repeated measures on task period. False positive percentages were log-transformed to correct positive skew. (Correct detection and RT measures were not strongly skewed and so were not transformed.) Box’s correction was used in applying $F$ tests when appropriate because of violations of the sphericity assumption. For correct detections, the main effects of cue, $F(1, 90) = 9.47$, $p < .01$, $\eta^2_p = .095$, and period, $F(2,479, 223,124) = 11.27$, $p < .01$, $\eta^2_p = .111$, were significant, but the interaction between these factors was not
EEG and Vigilance Decrement

Cuing elevated correct detections and detection rates declined across periods in both participant groups (see Figure 2). The only significant effect for false positives was the main effect of cue, $F(1, 90) = 8.31, p < .01, \hat{\eta}_p^2 = .870$. False positives were higher in the no-cue condition (8.46%) than in the cued condition (3.66%).

The analysis of mean RT showed a significant Cue × Period interaction, $F(2.841, 252.889) = 2.92, p < .05, \hat{\eta}_p^2 = .032$, but no main effects were significant ($p > .05$). RT was fairly stable across time in the cued condition but increased monotonically in the no-cue condition (see Figure 3).

Subjective State and Workload

A series of $2 \times 2$ (Cue × Pre- vs. Post-Task) mixed-model ANOVAs assessed effects of task parameters on objective state for the three DSSQ factors. For each factor, the effect of pre- versus post-task was significant at $p < .01$. $F$ values ($df = 1, 90$) were 81.23 (task engagement), 52.63 (distress), and 51.15 (worry). The corresponding $\hat{\eta}_p^2$ values were .474, .369, and .362. Relative to the pretask baseline, the effects of performing the task were to depress task engagement by −0.94 standard deviations, to elevate distress by 0.66 standard deviations, and to lower worry by −0.51 standard deviations. These main effects were not significantly modified by cuing ($p > .05$). Mean (and SD) for overall NASA-TLX workload was 5.67 (1.63) in the uncued condition and 4.89 (1.31) in the cued condition. These means differed significantly, $t(90) = 2.52, p < .05$.

Different EEG indices showed different patterns of response to the task parameters (see Figure 4). Alpha-1 and TLI showed complementary responses. Across task periods, alpha-1 power increased and TLI decreased, whereas providing the cue lowered alpha and elevated TLI.

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EEG Indices

A series of $2 \times 4$ (Cue × Task Period) mixed-model ANOVAs assessed effects of task parameters. There were no significant effects ($p > .05$) of the task factors on alpha-2. For the remaining indices, the main effect of period was significant for alpha-1, $F(2.116, 190.483) = 16.91, p < .01, \hat{\eta}_p^2 = .158$; for frontal theta, $F(2.814, 253.256) = 3.16, p < .05, \hat{\eta}_p^2 = .034$; and for TLI, $F(2.517, 226.496) = 3.29, p < .05, \hat{\eta}_p^2 = .035$; but not for EI. The effect of cue was significant for alpha-1, $F(1, 90) = 4.40, p < .05, \hat{\eta}_p^2 = .047$, and for TLI, $F(1, 90) = 4.18, p < .05, \hat{\eta}_p^2 = .044$, but not for the other indices ($p > .05$). The Period × Cue interaction was significant (or nearly so) for EI, $F(2.175, 195.745) = 2.92, p = .052, \hat{\eta}_p^2 = .031$, and for frontal theta, $F(2.814, 253.256) = 3.05, p < .05, \hat{\eta}_p^2 = .033$, but not for other indices ($p > .05$).

Different EEG indices showed different patterns of response to the task parameters (see Figure 4). Alpha-1 and TLI showed complementary responses. Across task periods, alpha-1 power increased and TLI decreased, whereas providing the cue lowered alpha and elevated TLI. (A reviewer of a previous version of this article questioned how closely temporal changes in performance coincided with changes in the two indices most sensitive to task period effects [alpha-1 and TLI]. To address this issue, we tested whether there was any evidence for nonlinear temporal trends by analyzing the polynomial contrasts for the main effects of period in the ANOVAs previously reported. The linear trend was significant for correct detections, $F[1, 90] = 19.23, p < .01$; alpha-1, $F[1, 90] = 26.54, p < .01$; and TLI,
By contrast, effects of task parameters on EI and frontal theta were interactive, not additive. For both the EI and frontal theta measures, cue/noncue differences were maximized in the fourth period but in different ways. Relative to previous periods, EI tended to increase in the cued condition but decreased in the uncued condition. By contrast, frontal theta increased in the uncued condition but remained stable in the cued condition.

Figure 4. Effects of task period and cueing on five electroencephalographic indices: alpha-1, alpha-2, Engagement Index, frontal theta, and Task Load Index. Error bars are standard errors.

$F(1, 90) = 4.90, p < .05$; but no quadratic or cubic contrasts were significant. Thus, it appears that all three measures change linearly over time, although future research using designs of greater statistical power may show more complex temporal trends.)
Interconrelations of EEG Indices

Table 2 summarizes correlational data. The leading diagonal of the table gives Cronbach alphas (in italics) for the four values available for each index from each task period. Values were high, demonstrating that interindividual differences were stable, despite changes in means during the vigil. The upper-right part of the table shows correlations for indices averaged across task period. TLI and frontal theta were substantially correlated, reflecting in part the place of theta in the numerator of the formula for TLI. Correlations between TLI and alpha were negative, as expected from the formula, but smaller in magnitude. EI was negatively correlated with both frontal theta and alpha, in line with the calculation formula. There was also a modest but significant negative association between EI and TLI. The lower-left part of the table shows the range of correlations across the four task periods, confirming that the associations between indices were fairly consistent across time. We also tested correlations between the NASA-TLX subjective workload measure and the EEG indices; no correlations reached significance (p > .05).

**DISCUSSION**

We examined effects of cuing and time on task on five EEG indices of alertness and workload during performance of a demanding vigilance task. Four indices were sensitive to effects of one or both task parameters, but they appeared to differ in their sensitivity to loss of vigilance over time. The alpha-1 index (lower-frequency alpha) showed the closest correspondence to performance and may thus be the most diagnostic of vigilance. We will consider further theoretical and practical implications of the findings.

**Theoretical Implications**

The vigilance task appeared suitable for testing predictions from resource theory (Warm et al., 2008). Similar to previous studies (Hitchcock et al., 2003; Matthews, Warm, Reinerman, Langheim, Washburn, et al., 2010), a substantial temporal decrement in correct detections was found, together with beneficial effects of cuing on performance. Subjective workload was higher in the uncued than in the cued condition, consistent with cuing reducing demands for attentional resources. Also, the task induced loss of subjective task engagement together with increased distress, the characteristic pattern of subjective state for vigilance (Matthews et al., 2013; Matthews, Warm, Reinerman, Langheim, Washburn, et al., 2010). However, cuing did not influence the magnitude of vigilance decrement in correct detections, although there was a differential decrement in mean RT. Possibly, signal detection deteriorated faster in the uncued than in the cued condition within the first 10 min, with no differential decrement subsequently.

EEG indices may be interpreted either as general measures of arousal and alertness (low alpha-1, EI) or as measures of excessive workload and effort generated by resource depletion (frontal theta, TLI). It was hypothesized that arousal/alertness indices would be lower in the uncued condition, so that over time, alpha-1 would increase and EI would decline. The prediction was confirmed for alpha-1 but not for EI. The greater diagnosticity of alpha-1 relative to
alpha-2 supports Klimesch’s (1999) division of alpha into two bands. Lower-frequency alpha (alpha-1) is associated with a topographically diffuse synchronization of activity across the entire scalp, indicating a generally inattentive state, which would correspond to poorer vigilance. Higher frequency (alpha-2) reflects more localized semantic memory processing, a cognitive function likely to be unimportant for sensory vigilance. Effects of task parameters on alpha-1 were similar to parameter effects on CBFV (Hitchcock et al., 2003), which has been interpreted as a measure of resource utilization (Warm et al., 2012). Alpha is generated by a thalamo-cortical circuit (Goldman, Stern, Engel, & Cohen, 2002; Klimesch, 1999), and brain-imaging studies confirm that thalamic afferents to various cortical sites are important for sustaining attention (Langner & Eickhoff, 2012). Functional magnetic resonance imaging studies suggest that although alpha desynchronization may be associated with change in the BOLD (blood oxygen level dependent) signal in various areas, one distinctive pattern is lower alpha power together with frontal-parietal activation (Laufs et al., 2006). Consistent with Langner and Eickhoff’s (2012) model, Laufs et al. (2006) identify frontal-parietal activation with higher vigilance.

The two effort indices, frontal theta and TLI (Gevins & Smith, 2003), were expected to be higher for the uncued task and to increase over time. These predictions were not supported. Frontal theta showed an interaction effect such that higher theta was observed in the uncued condition only in Period 4. Garcia et al. (2011) found temporal increases in frontal midline theta in a recent vigilance study, so further work on this index is needed. There were main effects of cuing and task period for TLI but opposite to those expected. TLI was higher when the task was less demanding, that is, in the earlier task periods and in the cued condition. This result contrasts strongly with previous findings that TLI increases with task demands. However, these studies (e.g., Gevins & Smith, 2003; Hockey et al., 2009) typically involved complex, multicomponent tasks requiring working memory that differ considerably in their processing demands from vigilance. The significance of TLI may depend on the nature of task demands. Given that TLI is inversely related to parietal alpha, its response to task parameters may be driven by arousal rather than effort in vigilance task environments.

Hancock and Warm’s (1989) model of sustained attention under stress may provide a framework for understanding the task dependence of EEG indices. Broadly, they differentiate hyperstress environments, in which high workload derives from the density and complexity of external stimuli, from unstimulating, hypostress environments, in which workload reflects demands on endogenous control of attention. TLI might reflect cognitive overload in hyperstress environments but adaptive efforts at controlling attention in hypostress environments. Conversely, elevations of alpha may be maladaptive under hypostress but not hyperstress conditions. Matthews and Amelang (1993) found no general association between alpha and performance deficit on a battery of short, demanding performance tasks. The concurrent decrease in EI and increase in frontal theta in Period 4 of the uncued condition might be interpreted as a sign of the dynamic instability with prolonged work under hypostress predicted by Hancock and Warm. Increased effort driven directly by failing vigilance (Smit et al., 2005) or “strain” (Hockey, 2012) may have appeared only after 30 min of maintaining steady though ineffective compensatory effort.

The correlational data also showed divergence between the indices. Instances of convergence, for example, between frontal theta and TLI, likely reflect the arithmetic interdependence of indices. Both EI and low alpha-1 were conceptualized as measures of general alertness, but they were only modestly related and could not be used interchangeably. The two effort measures (frontal theta, TLI) were more strongly correlated. The negative correlation between EI and TLI is consistent with the identification of both high EI and low TLI with greater fitness for performance (Freeman et al., 2004; Gevins & Smith, 2003), but the correlation magnitude was modest. Perhaps surprisingly, subjective workload, assessed with the NASA-TLX, was independent of the EEG indices. A similar finding from a different task domain was recently reported by Funke et al. (2013). Since both subjective and objective measures have been validated, it follows that
comprehensive workload assessment should include both “explicit” and “implicit” indices.

**Practical Implications**

Applied contexts in which diagnostic monitoring for vigilance may be important include vehicle operation (Matthews, Warm, Reinerman, Langheim, Washburn, et al., 2010), prolonged combat missions (Lieberman et al., 2005), and various jobs and industrial operations for which vigilance is requisite (O’Donnell, Moise, & Schmidt, 2005). However, the divergence of the various indices implies that choice of an EEG index for diagnostic monitoring of operator vigilance (Matthews, Warm, Reinerman, Langheim, Washburn, et al., 2010) is not simple. The data suggest that alpha-1 and TLI are both diagnostic of loss of attention and could be used to monitor operator functional state. Of these two indices, alpha-1 showed the larger effect size for the main effect of period; $\eta^2_p$ values were .158 and .035, respectively. In terms of Cohen’s (1998) $d'$, the effect size for change in the index from Period 1 to Period 4 (averaged across cue condition) was 0.41 for alpha-1 and 0.16 for TLI. Thus, alpha-1 may be preferable for applications. However, it is unclear whether the indices would perform similarly in relation to other types of vigilance task or other forms of sustained performance. TLI, in particular, behaved very differently here than in other studies in which high scores on the index were diagnostic of performance impairment (e.g., Gevins & Smith, 2003). Thus, use of EEG indices to diagnose impairment may require analysis of the moderator effects of task demands.

A key task factor in vigilance is whether the target discrimination is simultaneous (comparative judgment) or successive (absolute judgment). Successive tasks require working memory to integrate information across multiple displays and so may be more sensitive to resource depletion and vigilance decrement than simultaneous ones (Davies & Parasuraman, 1982; See et al., 1995; Warm et al., 2008). The current task (Hitchcock et al., 2003) is simultaneous, and it remains to be determined if EEG indices perform similarly for successive tasks. The sensitivity of TLI to working memory load (Berka et al., 2007) implies that the index might perform differently with a successive task.

Some features of the current study may limit its applicability. First, the task was selected because of its sensitivity to resource depletion, not as a work simulation. Thus, task duration was shorter than many operational tasks. Crowe, Dasari, Ding, Ling, and Zhu (2010) observed marked changes in EEG only after 70 min or so of continuous performance on an air traffic control simulation. Operational tasks, such as air traffic control, also include display monitoring as one of several task elements, which may influence the time course of neurocognitive change. Further work is needed to establish generalization of current findings to specific real-world tasks. Second, in keeping with the applied focus of the study, we analyzed broad indices of EEG response as defined in previous studies. Several authors (e.g., Baldwin & Penaranda, 2012; Christensen & Estepp, 2013; Wilson & Russell, 2007) have advocated training neural networks to infer workload from psychophysiological indices for the individual operator. Such approaches may be more discriminative of workload level than predefined indices. There are also more general advantages to using information from multiple physiological sources, not only EEG (Fairclough, 2009). Third, to our knowledge, this is the first study of vigilance using contemporary methods in a study conducted in Kazakhstan. Measures of performance and subjective state responses resembled those typically seen in Western samples (Warm et al., 2008), but there may be subtle cross-cultural differences in regulation of performance that influence EEG.

**Conclusion**

Different EEG workload indices are diagnostic of different aspects of the operator’s cognitive-energetic state. Thus, use of EEG indices for assessment of operator state requires an understanding of what each index signifies in relation to the task of interest. Further exploration of variation of diagnosticity with task demands is necessary before EEG indices can be generally utilized for applications.

**Key Points**

- Diagnostic monitoring for loss of vigilance is important in various human factors contexts. Multiple electroencephalographic (EEG) indices
of alertness and workload might be used for this purpose, but it is unclear which index is optimal.

- Data from an experimental study of sensory vigilance showed that lower-frequency alpha (8 to 10.9 Hz) was the EEG index that paralleled the vigilance decrement in performance most closely.
- The Task Load Index was also diagnostic of superior vigilance, but previous studies have linked this index to overload of attention.
- Frontal theta and the Engagement Index were sensitive to task workload only towards the end of the vigil.
- Spectral power of lower-frequency alpha may have applied utility as a diagnostic for operator vigilance.

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*Date received: June 03, 2013*

*Date accepted: December 05, 2013*