Chapter 22

Neural Efficiency Metrics in Neuroergonomics: Theory and Applications

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INTRODUCTION

There has long been an implicit understanding that effortful cognition is reflected by changes to brain activity; however, it is only recently with the advent of modern neuroimaging techniques that we have been able to study the relationship between mental workload and its neurological underpinnings. Cognitive psychologists have attempted to harness findings from neuroimaging studies to develop improved training and instructional methods that take advantage of the nature of cognition and its constructs. One particular perspective, cognitive load theory (CLT), proposes that the development of training and instructional methods must take into account the limitations of cognitive capacities, particularly working memory (WM), and that individuals learn most effectively when they allocate an optimal amount of cognitive resources.[1] With the understanding that increased mental effort increases metabolic demands on the brain, neural efficiency (NE) relates neurophysiological measures of brain activity to an individual's active cognitive demands, providing an indispensable link between CLT and accessible measures of neural activity for the measure of cognitive load. Importantly, NE helps capture how performance achieved under a specific cognitive load varies according to the demands of the task as well as the aptitude of the individual.

Reflecting a more global view of NE in cognition and intelligence, Haler et al. introduced the NE Hypothesis,[2] proposing that intelligent individuals have more efficient brain function and, as a result, reduced or more focused neural activity in a given task. Initial descriptions of this hypothesis were quickly amended under observations that measured efficiency was dependent on task difficulty[3] as well as domain knowledge that can be accumulated through practice and experience.[4] The more nuanced interpretation suggests that the intrinsic parameters of a person's cognitive abilities define both that individual's immediate performance on complex cognitive tasks as well as the rate at which they are able to acquire knowledge and develop successful strategies to improve performance. When combined with the viewpoint of CLT, this perspective demonstrates the potential of NE as a defining characteristic of an individual's latent ability as well as their capability to further develop their proficiency by enabling a more sensitive evaluation of individual's cognitive states during the process of learning and task performance. However, the measure of NE requires both contextual behavioral performance along with objective and continuous measures of cognitive load, which requires an understanding of both the cognitive and neurophysiological elements underlying task performance.

According to CLT, the optimization of cognitive resources must adhere to the general architecture and constraints of the WM system. WM, a subcomponent of the Executive system, consists of active memory that is maintained for immediate use during the performance of higher-order cognitive activities. Effective use of WM requires the active maintenance and contextual discrimination of task-relevant from task-irrelevant information to engage in goal-directed behavior.[5] This dynamic system is known to be intimately related with the construct of fluid intelligence, because performance on problem solving/reasoning ability is strongly correlated with WM capacity.[6] Therefore, WM represents a primary consideration in the development of training systems and an important limiting factor on the ability of individuals to transfer knowledge and acquire complex skills.

Although an individual's intelligence may be described in part by WM capacity, CLT suggests that the quantity of the WM resources that are devoted to the task or learning process has a greater effect on how much information is learned and

Neuroergonomics. https://doi.org/10.1016/B978-0-12-811926-6.00022-1

retained. Failures of task learning therefore occur when either the demands of the task exceed available capacity, or there is insufficient allocation of mental resources to the task. These conditions of cognitive overload and underload, respectively, are presumed to be liable for task-related performance degradation during both training and execution. Thus the development of training paradigms could employ well-defined measures of cognitive exertion to refine their procedures such that they maintain optimal cognitive allocation and ensure effective task transfer. To do this, techniques for objectively assessing cognitive load must be combined with behavioral performance metrics in a manner that enables the quantification of training efficiency.

Researchers have explored multiple methodologies in the attempt to extract metrics of cognitive load. Rating-scale techniques are by far the most commonly employed techniques due to their ease of application and low-cost nature.[7,8] Despite their utility, these techniques suffer in their reliance on subjective introspection on the part of the participant, as well as the fact that they cannot operate continuously and remain unobtrusive. To address these issues, physiological measures have more recently been studied in the search for continuous and objective measures of cognitive load. Measures such as heart-rate variability and blink rate have primarily been investigated as alternative and complementary measures to rating scales[1] due to their low cost and ease of application, but these techniques lack specificity and, in the search for more specific measures, researchers have turned toward the brain.

Direct measures of brain activity through noninvasive neuroimaging techniques such as functional magnetic resonance imaging (fMRI) and positron emission tomography have revolutionized neuroscience and clinical findings; however, the relatively high cost of these techniques along with restrictions on experimental environment and participant behavior have prevented their direct use in practical applications.[9,10] Fortunately, in recent years, portable noninvasive neuroimaging techniques have dramatically increased their technological capabilities and overall affordability. Measures of brain activity through techniques such as electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) may allow a more direct, specific, objective, and continuous assessment of cognitive load required to monitor and adapt training paradigms.[11,12] Both fNIRS and EEG offer distinct advantages due to their ability to measure in both controlled and natural environments, giving promise for roles of noninvasive neuroimaging outside of the laboratory context.[13]

MEASURING NEURAL CORRELATES OF COGNITIVE LOAD: ELECTROENCEPHALOGRAPHY

Electroencephalography relies on the measurement of changes in electric potentials across the scalp, attributed to cortical activity by the underlying neuronal populations.[14] Devices capable of measuring EEG signals can be manufactured at increasingly lower costs, and recent availability of open-hardware platforms have allowed individuals to build their own devices. The major advantages of this technology are that the measurement of interest has a rather high time resolution (~1 ms) and that only a few channels are needed to generate useful cognitive load discrimination. A large number of studies detailing the use of EEG systems to measure mental workload have been published,[11,14–17] and this technique has been at the forefront for development of brain–machine interfaces [11,18] and has demonstrated superiority to peripheral physiological research.[11]

This flexibility of EEG systems to measure cognitive activity in a variety of circumstances has made the technique a popular tool in neuroergonomic and neurocognitive research with a pathway to practical public adoption.[16] EEG measures of workload are conventionally divided into either measurement of the power spectral densities (PSDs) or amplitudes derived from event-related potentials (ERPs). PSD measures are calculated from the power spectrum and typically divided into the alpha (8–13 Hz), beta (13–30 Hz), delta (1–4 Hz), theta (4–8 Hz), and gamma (30–50 Hz) bands. The alpha band has been extensively studied due to its sensitivity to attention and workload.[19,20] Although decreases in alpha activity are positively correlated with increase in task demand and related to attentional processes, their decreases are also often paired with increases in theta-band power,[17] and often this conjunctive relation with alpha power is used as an estimation of workload.[14,21] Furthermore, individual differences in alpha frequency have commonly led investigators to divide the alpha band into two subbands based on the individual alpha frequency,[21] on which the upper alpha band is thought to predominately reflect cognitive ability. Through the measure of temporal changes in band power as reflected by event-related desynchronization and synchronization, increases in workload can be related to both general and individualized alpha measures[20] and may be used to continuously monitor performance and workload. On the other hand, ERP measures concentrate on the average of evoked responses due to stimuli such as the amplitudes of the N100 and P300, which occur at approximately 100 ms and 300 ms, respectively. The P300 amplitude in particular is a demonstrated measure of attention and workload,[14,22] whereas P300 latency instead reflects speed of processing, another important factor in cognition.[23] Although powerful, ERP measures are often more difficult to make in real-world environments due to the requirements of stimuli needed to probe the cognitive state and averaging needed to reduce response variability. In addition to these classical methods, measures such as functional connectivity and others derived from graph theory have opened new area of investigation with the promise of more informed and more sensitive measures.[24–26]

MEASURING NEURAL CORRELATES OF COGNITIVE LOAD: FUNCTIONAL NEAR-INFRARED SPECTROSCOPY

Functional Near-Infrared Spectroscopy (fNIRS) is a more recently developed technique that is capable of measuring the localized changes in oxygenated (HbO) and deoxygenated (Hb) cortical hemoglobin that occur because of cerebral activity.[10,27] These blood-flow changes, termed the hemodynamic response,[28] are the result of coupling between the neurovasculature and metabolic demands of neurons in response to increased activity. fNIRS takes advantage of the relative transparency of tissue to near-infrared light to provide quantification of the changes in relative hemoglobin, thus reflecting the metabolic demands of the brain.[29] Although hemodynamic activity does not occur as quickly as electrophysiological events (4–5 s vs. ~1 ms), fNIRS provides distinct advantages in terms of its ability to detect localized activity, resistance to motion artifacts, and potential to translate shallow cortical biomarkers discovered using fMRI into practical application, thanks to similarity in the measurement used.[30,31] Although fMRI describes activities in terms of the Blood Oxygen Level Dependent (BOLD) response, highly correlated with Hb, measurements using fNIRS can record these neural activities as increases in HbO, decreases in Hb, or as changes between these two parameters such as oxygenation (Oxy) and total hemoglobin (HbT) content. fNIRS systems are capable of measuring surface cortical areas corresponding with numerous functional roles; however, fNIRS systems are particularly well suited for the study of workload due to their ability to conveniently measure the prefrontal cortex (PFC), an area intricately linked with cognitive load and WM.

Through neuroimaging and classic neuroanatomic studies, the PFC has consistently been ascribed roles in WM and the underlying organization of high-level information.[32,33] In one WM model, Repovš and Baddely[34] theorized that WM is constituted from four components including two unimodal storage systems (the phonological loop and visuospatial sketchpad), an episodic buffer for the integration of information, and a central executive responsible for the manipulation of information and the coordination of the unimodal storage systems. The overlap of functionality between this central executive component and the role of the PFC has guided researchers in efforts to map the functional architecture of the PFC. fMRI evidence has suggested a hierarchical relationship between the dorsolateral (dlPFC) and ventrolateral (vlPFC) PFC regions, with the dlPFC responsible for monitoring and identifying task-relevant representations and the vlPFC maintaining those representations.[35] This balance between organization of WM and the maintenance of it was supported by another study examining differences between structured and unstructured sequences, which reported that the consolidation of information to reduce WM load or "chunking," increased vlPFC recruitment.[36] The vlPFC has also been implicated in the retrieval of information,[37] as well as the intention to retrieve.[32] Another area of note, the anterior PFC (encompassing Brodmann's area 10 [BA10]) has been described as the single largest cytoarchitectonic area in the PFC.[38] In humans, BA10 has evolved to be approximately twice relative size in comparison to other primates, leading to intense speculation regarding the roles it plays in human cognition.[39] These roles have ranged from the internal processing of emotions and internal states (mentalizing), to memory retrieval, prospective memory, attentional control, and relational knowledge.[38] Additional metaanalytic work has suggested that the medial–lateral hierarchical organization could be found within BA10 as well, with lateral activity disproportionally associated with memory retrieval and medial activity associated strongly with "multitasking," encompassing executive functions of task-switching, planning, and goal orientation, being associated with medial structures.[40]

The richness of the PFC as an area sensitive to parameters of task complexity, WM load, emotional processing, and planning is a great benefit to fNIRS studies. In particular, due to the natural absence of hair on the anterior PFC, a large area is made more accessible to fNIRS, greatly expediting setup time, reducing system complexity, and often allowing more ecologically valid measurements. Using fNIRS, researchers have validated the relation of PFC activation and WM load under controlled conditions using standardized WM tasks such as the N-Back task.[12,33] The N-Back is a graded demanding memory task that requires the participant to pair stimuli with prior stimuli in a sequence. In fMRI, the N-back has been found to broadly activate the dlPFC, anterior PFC, and vlPFC, with variations in functional specialization according to task-specific modifications.[32] Supporting this, fNIRS has demonstrated sensitivity to various workload levels of the N-Back task with observations of linear increases in HbO,[12] increases in interhemispheric dlPFC connectivity,[41] and, in a visuospatial variant, linear decreases of Hb.[42]

Reliable workload measurements in controlled laboratory conditions using fNIRS have encouraged researchers to generalize these findings to real-world environments and found considerable success under a variety of complex tasks. In one study, Ayaz et al. monitored PFC activity in air traffic controllers who were tasked with supervising an increasing number of virtual aircraft. The results showcased linear changes in left-dlPFC HbO paralleling workload changes observed in the N-Back task.[12] These changes were also significantly correlated with self-reported National Aeronautics and Space Administration–Task Load Index (NASA-TLX) workload, bolstering evidence for the capability of fNIRS to measure workload objectively. Another neuroergonomic study, on the operation of an endoscopic simulator performed by James et al., showed increased lateral PFC activation in expert operators and increased oxygenation in response to more challenging navigation.[43] In a real-life driving task, Yoshino et al. observed that moments that required rapid deceleration were followed by increased cognitive load in BA10 as noted by increased HbO.[44] Similarly, during flight-simulator operations, increased HbO during difficult landings in the initial trial versus reduced HbO observed in the final trial,[45] implied that reduced task demand was observed with practice.[12] Although challenges of continuously measuring workload during prolonged and fatigued states still remain,[46] and the linearity of fNIRS response to workload increases remains an oversimplification,[47] these trends point toward opportunities to develop more-robust statistical methods and imaging technologies as potential solutions.

One such approach might be to combine multiple workload assessment strategies to help identify variabilities and extremes within different operational contexts. In particular, the fact that fNIRS and EEG offer orthogonal perspectives on neural activity has prompted researchers to explore the particular advantages of each technique, as well as the way in which they complement each other. Several studies have explored the use of hybrid neuroimaging strategies reporting enhanced classification accuracy on workload of WM tasks,[48,49] and mental states during the operation of motor vehicles.[50] Although the combination of modalities currently increases complexity both of setup and analysis, future refinements in both technology and methodology may make hybridization a practical and even natural choice, allowing for a more comprehensive assessment of mental workload and operator state.

CALCULATING AND EMPLOYING MEASURES OF NEURAL EFFICIENCY

The goal of NE analysis is to quantify the otherwise hidden relationship between neural activity and performance among individuals over time, under varying task conditions, or alternatively across populations. In this way, NE analysis naturally extends the efficiency view,[51] which states that the relationship between mental effort and performance is subject to many variables of interest such as task parameters, environmental conditions, and individual ability. Under highly efficient conditions, performance is significantly higher than what would otherwise be expected given a specific neural load. On the other hand, inefficient conditions are marked by increased neural load and lower-than-expected behavioral performance. Although a preserved positive effort-to-performance relation is still presumed, efficient systems benefit more in terms of performance per relative measure of neural effort. As a result, efficiency and inefficiency are judged by how far the neurobehavioral measures deviate from the normal effort-to-performance relationship. By measuring the way in which variables of interest impact this effort-to-performance deviation, their impact on overall efficiency can help inform system design and gain insight on the task condition or individual involved.

Behavioral metrics of performance and neural correlates of workload often cannot be directly mapped in a manner that preserves the value and context of their relationship in an individual or system. Therefore, prior to the calculation of efficiency, these individual measures must first be normalized according to the group of interest. Adapting the definition first described by Paas et al.[52] to the context of neural measures, NE is calculated as the projection of normalized (z-score) behavioral performance (P) and brain-derived measures of cognitive effort (CE) onto the identity axis as seen in Fig. 22.1. Converting both behavioral and neural measures into normalized measures allows a clear and comparable interpretation of the immediate measures and their relationship. In this relationship, average neural effort and behavioral performance will by definition be achieved at the origin (0,0). Given the normalized values of each condition, equivalent relative efficiency can be expected to be achieved along the identity line (CE = P) which by definition would have a mean NE of zero. Along this line, performance one standard deviation from the mean would be expected to demand neural effort one standard deviation from that mean. NE can therefore be measured as the distance away from or projection onto the NE identity line as defined in Eq. (22.1). This equation is identical to the definition previously proposed,[52] except with the additional stipulation that measures of mental effort are derived from a linearization of neural measures.

$$\mathrm{NE} = \frac{z(\mathrm{P}) - z(\mathrm{CE})}{\sqrt{2}} \tag{22.1}$$

To compare the relative efficiency of conditions, as the method was initially described, neural measures and performance (CE, P) should be normalized according to the collected measures of all conditions inclusively. Following this, the new NE metrics can be statistically compared similarly to the original metrics providing they satisfy the assumptions of the statistical test employed.

To explore the way in which NE metrics can be calculated and analyzed, we present results from an earlier study in which 24 healthy participants completed an N-Back WM task at various difficulty levels (0-Back,1-Back,2-Back, 3-Back), while their prefrontal activity was monitored with fNIRS.[53] Throughout the task, we had reported that increases in WM demand resulted in both increased prefrontal oxygenation from baseline in the left dlPFC and decreased behavioral performance. These results are typical of findings from the N-Back WM task and here are presented as an example of neuroefficiency

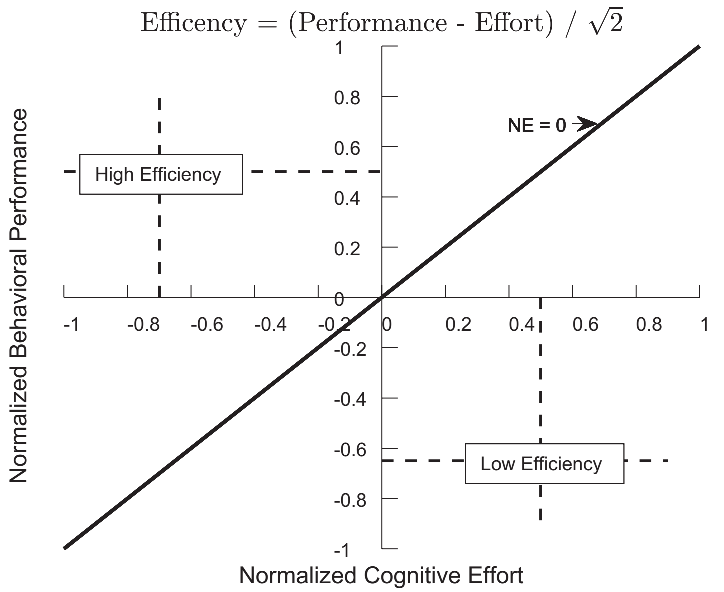

FIGURE 22.1 Neural efficiency in relation to cognitive effort (CE) and behavioral performance (P). High-efficiency quadrant contains relatively low neural demand that results in relatively high behavioral performance, and the low-efficiency quadrant contains the opposite observations.

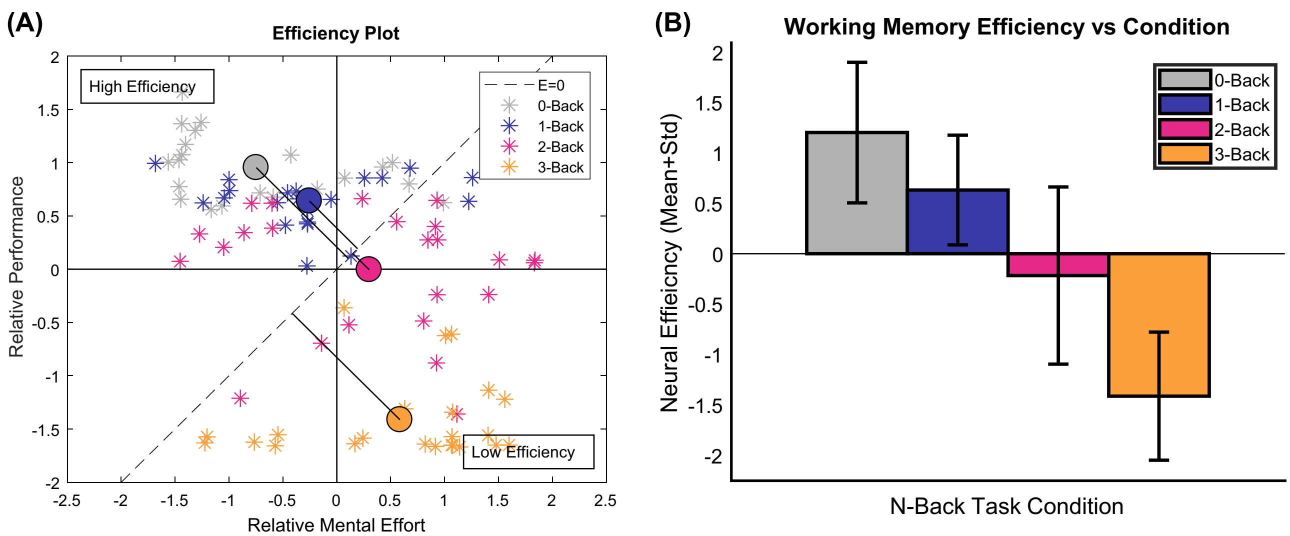

FIGURE 22.2 (A) Normalized oxygenation versus normalized accuracy during the N-Back task. Condition means are indicated by the weighted circles. (B) Mean NE for each N-Back task condition.

analysis as shown in Fig. 22.2. First, N-Back accuracy and prefrontal oxygenation are normalized across all task conditions and participants. Second, NE measures are calculated for each respective trial using Eq. (22.1). Third, newly calculated NE measures are assessed for a main effect of condition using analysis of variance (ANOVA). Fourth, following a significant main effect, planned post hoc tests are performed to evaluate differences between specific conditions.

DISCUSSION: APPLICATION, CHALLENGES, AND LIMITATIONS

In the present sample dataset, we illustrate how NE metrics reflect changing efficiency with increased workload. Clear differences in NE are observed as participants experience increasing WM demand with a trend towards a decrease in efficiency in the presence of increased difficulty. These results show how difficult conditions require a higher investment of effort to maintain performance relative to less demanding conditions. Although the calculation of efficiency metrics is a straightforward mathematical process, interpretation of the results may be more subjective. In this case, the clear changes of both P and CE per Condition strengthen the argument that changes in NE between conditions are statistically significant as well. However, although strength of NE assessment is the increasing sensitivity to conditions that impact the relationship between performance and demand, this may result in significant changes in NE in the absence of significant changes in either P or CE. Whether portrayed as an increased sensitivity to experimental parameters or simply as an additional interpretive perspective, efficiency measures should always be presented and analyzed in the context of the nonnormalized measures that form the basis for the analysis so that the results and implications can be understood in an objective way.

Importantly, NE metrics inherently draw on the reliability and utility of the sensitivity of both the employed CE and P scales. Therefore, any ambiguity inherent in either measure will also present itself within NE analysis. Although many times performance scales for specific tasks are well characterized, neural measures of cognitive workload are an area of ongoing investigation and their behavior across populations and within individuals is often variable. Due to uncertainty of the nature of both scales, NE scores should be compared with some caution even when identical in magnitude and direction. The notion that linear changes in effort result in linear changes in performance rests on the assumption that both scales behave in a linear fashion.[54] With enough knowledge or calibration of the underlying scales, it may be possible to linearize measures of CE and P such that these assumptions are met consistently. This, however, remains a rather substantial challenge, because even the way in which the methodology employed to assess activation may bias workload calculations and therefore the resulting efficiency calculations.[55] Therefore, further improvements in neuroimaging methods and methodologies are needed to not only improve the stable measurement of NE measures, but also enhance their usability as characterizations of cognitive performance.

Although in this example "Condition" refers to the experimental parameter of the task itself, by normalizing scores or neural measures with respect individual subjects across multiple trials it becomes possible to derive NE metrics that may describe differences in individual participant's performance and/or behavior across trials. The ability to use NE metrics as a characterization, not just of a system's behavior, but an individual's capacity within that system, may be a hidden strength of NE analysis. In part, normalization of scales within an individual may remove substantial uncertainty from the assumptions present in NE comparisons introduced by intersubject variability. Individual NE analysis may also play an important part in characterizing an individual's cognition and adaptation of systems or training to their individual strengths.

CONCLUSION

Neuroergonomic design and research benefit substantially from an understanding of the elements that make up individual differences in human cognition and performance. NE, in this case, is a measure that gives meaning to measures of cognitive load by showing how they relate to outcomes of interest. Presently, the use and application of NE analysis is an area of ongoing investigation. However, as neuroergonomic techniques to monitor cognitive workload mature in terms of reliability and usability, an understanding of the relationship that drives translation of CE into tangible performance may well become an integral part of system development. Under these circumstances, a well-designed system could be built in a manner that allows system operators to operate efficiently without exceeding or fatiguing available cognitive resources. On the other hand, well-designed instructional techniques may use NE metrics to enhance learner's information-processing abilities, potentially shortening required training times. Intelligent design using NE characterization offers a substantial and tangible goal for the development of individualized, optimized systems and training that enhance both learning and performance outcomes.

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Section **IV**

Neurostimulation Applications