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Tutorials

Understanding the role of cognitive effort within contextual interference paradigms: Theory, measurement, and tutorial

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ABBREVIATIONS

CI	Contextual interference
$biomk_j$	Biomarker of interest
BLK	Blocked
CLT	Cognitive Load Theory
EEG	Electroencephalography
fMRI	Functional Magnetic Resonance Imaging
fNIRS	Functional Near Infrared Spectroscopy
fe_i	Feature of interest
HbO	Oxygenated hemoglobin
HbR	Deoxygenated hemoglobin
i	1…n
j	1 to 4
L	Left region of interest or channel
LI	Laterality index
MD	Maze distance
R	Right region of interest or channel
RND	Random
RNE	Relative neural efficiency
RNI	Relative neural involvement
PFC	Prefrontal cortex
ΔHbT	Total hemoglobin

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BACKGROUND: "Contextual interference" (CI) describes a counterintuitive phenomenon related to practice organization when learning multiple tasks that are presented in a non-repetitive order. In CI, the lack of repetitiveness introduces a high level of interference (e.g., random practice) within the learning context such that task performance during initial skill acquisition is frequently poorer than if tasks are practiced in a repetitive fashion. However, these learners often perform better on retention and transfer tasks than individuals who learn within a low CI environment (e.g., blocked practice). High CI acquisition settings require large amounts of cognitive effort; however, the majority of research has focused on measuring behavioral outcomes rather than directly investigating cognitive load and its relationship to performance.
AIM: In this paper, we provide a tutorial on several novel ways in which researchers can investigate brain activity in a CI paradigm using functional near infrared spectroscopy: Relative neural efficiency (RNE), relative neural involvement (RNI**),** and laterality index (LI).
METHOD: RNE integrates measures of cognitive effort and behavioral performance; in high CI learning environments, RNE should initially be poor (high cognitive effort, low behavioral performance), then improve during retention and transfer. RNI provides an index of the relationship among motivation, mental effort, and performance. Finally, LI allows for the exploration of lateralization between the two hemispheres of the cerebral cortex. We provide data-based examples of RNE, RNI, and LI to demonstrate their usefulness in understanding the effects of CI on cognitive load.
RESULTS: Significant differences were found for total hemoglobin (μmolar), RNE and LI for the right and left prefrontal cortex regions ($p<0.05$). The differences were accompanied by moderate-to-large effect size (Hedge's $g>0.666$) with random using less effort, better performance and was more oriented to goal orientation and learning processes than blocked who focused more on visuomotor attentional components and used more effort with lower behavioral performance scores.
CONCLUSION: RNE, RNI, and LI provide innovative methods to better understand cognitive effort within CI paradigms.

KEYWORDS: Cognitive Load | Prefrontal cortex | Motor learning | Conditions of practice

INTRODUCTION

The term "contextual interference", originally identified by Battig[1] in 1966, describes a counterintuitive phenomenon related to practice organization typically within an initial learning environment and its relationship to motor learning. The contextual interference (CI) effect results from the organization of practice when learning multiple tasks that are presented in a non-repetitive order. Here, the lack of repetitiveness introduces a high level of interference within the learning context (hence the name "contextual interference") such that task performance during initial skill acquisition is frequently poorer than if tasks are practiced in a repetitive fashion. However, these learners often perform better on retention and transfer tasks than individuals who learn within a low contextual interference environment[2,3]. Since the 1970's, researchers have examined the contextual interference effect in motor learning, based on practice organization when learning multiple tasks[4–6]. Within a traditional CI research paradigm, learners are presented tasks in either a blocked (BLK) or random (RND) order during task acquisition. BLK represents a learning environment with low CI; individual skills are presented to the learner repeatedly for a fixed number of trials within a task block. The task predictability and repetition within a block leads to both high performance and seemingly 'fast' acquisition for the specific skill. Conversely, learners in a high CI environment, while performing the same number of trials within a block, are exposed to multiple tasks in a non-sequential, unpredictable, interleaved order (e.g., RND). RND practice results in high CI and concomitant lower performance during acquisition than BLK learning. While acquisition performance suggests superiority of BLK scheduling, retention and transfer tests indicate otherwise. In fact, the high CI that learners experience in the RND group appears to ultimately enhance skill learning[7,8].

By their nature, high CI acquisition settings require large amounts of cognitive effort. To date, the majority of research has focused on measuring behavioral outcomes rather than directly investigating cognitive effort as a function of CI. Only in the past 15 years have researchers had the methods to explore the neural underpinnings of the CI effect using brain imaging techniques[7,9–13]. When studying motor learning, brain imaging approaches become more complicated because functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) devices are highly sensitive to motion artifact, restrict movement, or can be cost prohibitive (especially fMRI). Pinti and colleagues[14] compared fNIRS with other neuroimaging modalities on several parameters including cost where fNIRS and EEG are relatively low in cost in comparison to the high cost of fMRI and PET. In recent years, functional near infrared spectroscopy (fNIRS) has become a popular alternative to these techniques. As a noninvasive, optical brain imaging tool, fNIRS allows researchers to monitor changes in hemodynamics within the prefrontal cortex (PFC) related to different cognitive loads. Several studies have looked at the CI effect within a cognitive load theory (CLT) framework using fNIRS technology. For example, Shewokis and colleagues[12]examined the CI effect in ten medical students who were learning laparoscopic surgical techniques via simulation, with half receiving blocked and half receiving random practice schedules over four days. Performance measures were tracked and coupled to hemodynamic responses during skill acquisition, retention, and transfer. Behavioral and outcome data indicated a CI effect occurred in that the random group performed better in retention and transfer, and analysis of oxygenated hemoglobin indicated this behavioral performance benefit was associated with lower oxygenated hemoglobin change in the right dorsolateral PFC than the blocked group.

THE PREFRONTAL CORTEX (PFC)

The prefrontal cortex (PFC), the most anterior portion of the frontal lobe, plays an important role in executive function processes and is particularly important in the early, stages of learning such as experienced during the acquisition phase during a CI paradigm. The PFC plays a key role in planning complex cognitive behavior, decision making, and attentional control, among other functions[15–19]. Of particular interest within CI paradigms are the high-level executive function processes associated with the PFC fundamental to completion of goals with associated behaviors such as anticipation, goal establishment, result monitoring, action inhibition, and planning[20,21]. Further, the PFC outlines the execution of programmed sequences of actions and its consequences[22]. Therefore, active representation of future events resulting from behavioral actions are within the realm of the PFC functions, all within a problem-solving structure.

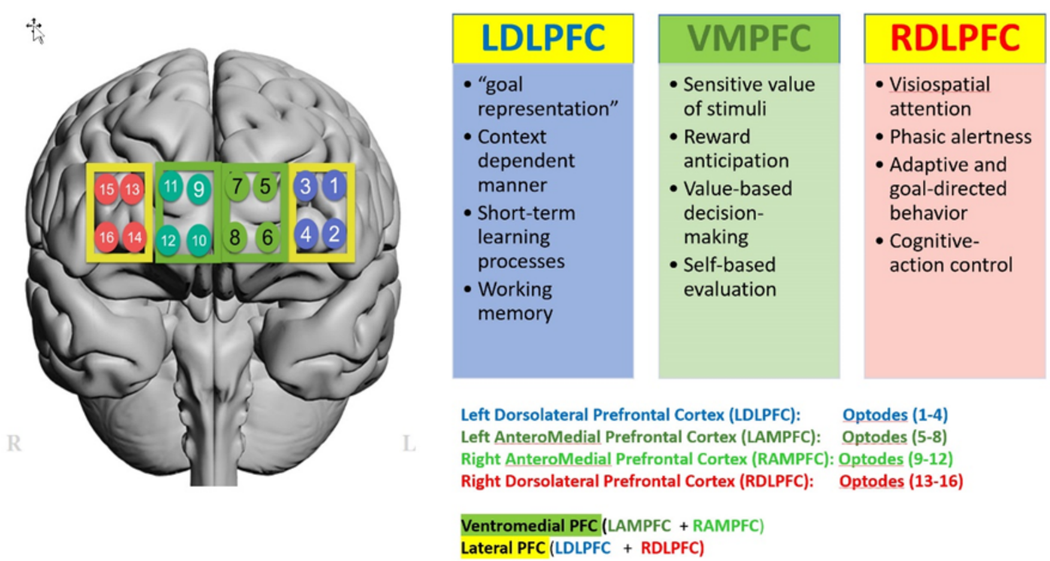

Figure 1. The prefrontal cortex and regions of interest with their associated functions[17,19, 21].

THE PFC, COGNITIVE LOAD, AND FNIRS

Functional Near-Infrared Spectroscopy (fNIRS) is a neuroimaging tool that is non-invasive, portable, affordable, and safe for continuous and repeated measurements (Figure 2). fNIRS indirectly measures neural activity using the physiological principles underlying neurovascular coupling (i.e., relationship between neuronal activity and cerebral hemodynamics) which then allows for interpretation and understanding of task-related activities[23,24]. Physiologically, neurovascular coupling is based on the oxygen requirements and the delivery of oxygen that is used for glucose metabolism via neurons in the neuronal activation process. The process of increased neuronal activation yields increased cerebral blood flow that carries oxygen to the region of use/need through oxygenated hemoglobin (HbO). This HbO is converted to deoxygenated hemoglobin (HbR) when oxygen is released. To this end, HbO and HbR are the principal absorbers of near-infrared light for fNIRS applications in which HbO and HbR are used to measure relative concentrations of the various biomarkers and then applied in brain activity assessments during the performance of tasks.

The application of fNIRS involves multiple signal preprocessing techniques to remove artifacts. These techniques include high pass and finite impulse response low-pass filters that use cutoff frequencies of 0.005 Hz and 0.09 Hz to aid improvement with removal of instrument and physiological noises and to improve spatial sensitivity and specificity. Signal quality and channel rejection was done by assessing saturation of signals along with high noise levels. After the artifacts were removed and high noise channels rejected, a modified Beer-Lambert Law was applied to the signals to determine the optode (channel) specific measures (16 optodes/channels) for HbO, HbR, Oxygenations (HbO – HbR) and HbT (Hb Total = HbO + HbR)[19,25]. The use of functional near infrared spectroscopy, by providing measures of hemodynamic change occurring within the prefrontal cortex, is a non-invasive way in which to examine the learning process and intervention efficacy at the level of the brain[18,26]. When combined with the behavioral data, fNIR can provide information about cognitive load changes, such as improvements in relative neural efficiency and involvement[13,27].

Figure 2. fNIRs sensor pad designed to collect oxygenation data from the prefrontal cortex. The upper picture shows a series of light sources and detectors. The lower picture depicts a participant wearing the fNIRs sensor pad before data collection.

Therefore, it is the purpose of this tutorial to provide both a foundation for researchers interested in delving more deeply into CI paradigms to better understand the underlying neural mechanisms in the performance and learning processes. We specifically focus on using fNIRS to measure cortical activity because it is more motion tolerant than other brain imaging techniques and further, is relatively inexpensive, accessible, and easy to learn. We begin by reviewing CLT, then discuss different ways to measure cognitive effort within a CI paradigm, and finally, we provide several applications for use.

UNDERSTANDING COGNITIVE EFFORT WITHIN DIFFERENT CI LEARNING ENVIRONMENTS: COGNITIVE LOAD

One promising theoretical perspective related to instructional strategies that may provide insight into the CI effect is Cognitive Load Theory [28,29] (CLT). Task learning and performance places a burden on a learner's working memory, which has been termed cognitive load. According to CLT, differences in cognitive load that learners experience within various instructional environments may result in distinct learning outcomes. CLT suggests that three forms of cognitive load exist: intrinsic, extraneous and germane[30–33] (See Figure 3). Intrinsic load relates to the inherent quality or complexity of a task or knowledge to be learned; this interacts directly with the learner's expertise and ability to understand new information[12]. Extraneous load is not associated to the task itself, rather it concerns other factors that indirectly affect the learning process, such as how the information is presented, or instructional procedures used[32]. Finally, germane load communicates specifically to the learning process and the mental effort or cognitive resources required to learn a task. Learning paradigms that enhance germane load during skill acquisition allow for the positive transfer of previously learned information to assist in the construction of new skills.

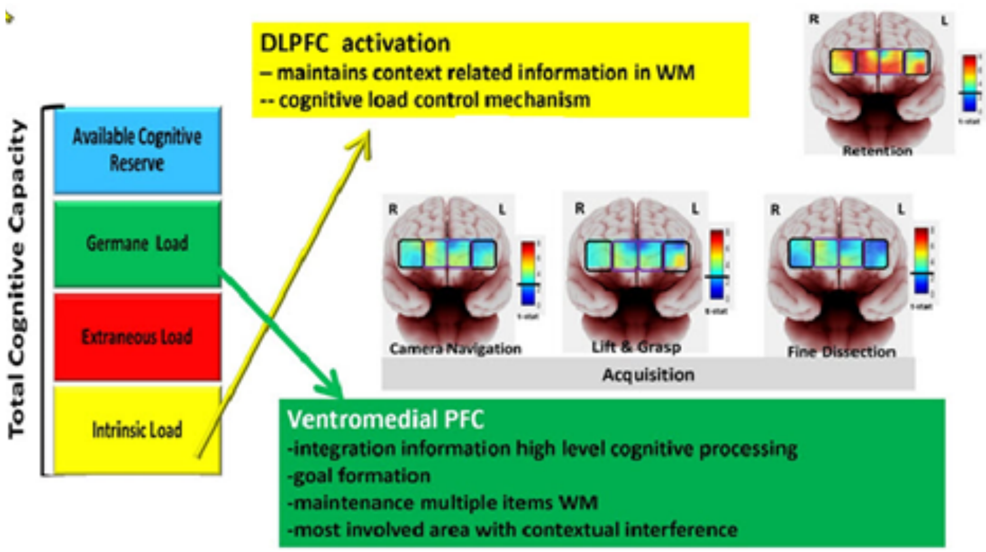

Figure 3. The different types of cognitive load[29,30] and their associated regions within the prefrontal cortex[9,12,13, 20,23, 26,39].

Paas and colleagues[28,34] noted that an instructional strategy that encapsulates both cognitive and motivational effects on learning is variability of practice. Contextual interference is considered a type of practice variability when learning multiple tasks. In a recent review, Czyz[35] compared and contrasted the differences of practice variability in Schmidt's Schema Theory and the contextual interference effect. Variability, according to Schmidt's Schema Theory, occurs during practice that involves multiple variations of a motor skill that is associated with the same class of movements. Conversely, CI has extended practice variability as motor skill variations may occur within a single class of movements or across multiple classes of movements. Thus, the level of variability depends upon the motor skills being tested in a CI paradigm[35]. Considering CI and having an instructional strategy that can be used to modulate the presentation of task dynamics that can inherently reflect realistic learning environments is critical for our understanding and applications of the dimensions of CLT27,[29,36]. The advantage of a RND practice schedule during acquisition is that the changing presentation of the task demands increased cognitive effort and increased motivational involvement from the learning which results in more effective schema construction than a BLK practice schedule which has minimal task changes[3,5]. It is well established that learning is best exemplified by assessments of generalization or transfer[8,37]. Given that high CI or RND practice is a form of increased variability of practice relative to a BLK order, it is expected that RND practice would facilitate the recall and generalization of acquired cognitive schemas and would result in improved transfer.

MEASURING COGNITIVE LOAD WITHIN A CI PARADIGM

Researchers who have studied the CI effect consider practice organization with high CI a type of practice schedule variability when learning multiple tasks[3,8,13,37]. Paas and colleagues[28,36] developed several subjective measures as a means to better understand the relationship between cognitive workload and performance output that have potential in exploring brain and behavior relationships within a CI paradigm. The first was termed "relative efficiency", which measures the efficiency of one's cognitive effort while performing different cognitively challenging tasks; the focus of their work was on the application of cognitive effort during the learning of multimedia tasks using a subjective effort measure. From their perspective, a high relative 'cognitive' efficiency value indicates that an individual performed better with a relatively lower amount of cognitive effort. This increased efficiency represents an increase in learners' skill acquisition by using fewer cognitive resources after adequate training and has been applied using more objective measures of cognitive effort (e.g., brain imaging) in different environments including simulations and virtual learning[13].

RELATIVE NEURAL EFFICIENCY

Optical imaging technology like fNIRS has seen increased use and development of mobile, miniaturized devices that are non-intrusive[38]. These technological advancements increase the potential for fNIRS to be used in many real-world learning environments to provide objective, task related neural measures of cognitive effort that include behavioral and performance measures for an integrated assessment of the learning process across different instructional strategies or (e.g., task types and difficulty levels, practice and feedback variables, and levels of expertise – novices vs. expert performers). The use of fNIRS has allowed for a more precise measure of cognitive effort in this Paas' formula, allowing for the calculation of relative neural efficiency (RNE). RNE combines measures of behavioral output with measures of underlying cortical activity (particularly in the prefrontal cortex), thereby quantifying cognitive effort as it relates to performance.

RELATIVE NEURAL INVOLVEMENT

Additionally, relative neural involvement (RNI) is another measure that provides a gauge of motivation within a task setting. This measure, originally defined as cognitive involvement, uses similar calculations as RNE but with a different approach to interpreting the results. This RNI approach utilizes the assumptions that motivation, mental effort, and performance are positively related and when applied to a novice learning environment, it can help to identify which instructional conditions promote better motivation and therefore overall performance. This novel motivational theory stems from the CLT, which entails both mental effort and performance, the resultant physical effort, as primary components. This follows the understanding that when learner involvement is higher in a specific task, more mental effort is likely being invested. For example, Koiler et al.[27] determined that, when performing the non-assembly tasks on the Purdue peg test, individuals with ADHD who used a fidget spinner performed similarly and had similar levels of RNI to all age-matched controls. By comparison, the ADHD control group had significantly lower levels of RNI than all other groups. In this case, control participants matched effort and performance, whereas in the ADHD groups, the introduction of a fidget spinner appeared to improve overall motivation as well as performance.

Hypothetical examples of RNE and RNI are presented in Figure 4. The perpendicular distance from the neutral efficiency condition, E = 0, where Performance = Effort, to each of the points plotted on the Performance–Effort axis is the efficiency value for that group. Thus, this graph provides an especially useful visual display of the efficiency, effort and performance relationships.

WHAT RNE AND RNI TELL US

Constructing learning protocols involves careful examination of the components of intrinsic load, namely, task characteristics, learner characteristics and the interaction of task characteristics and learner characteristics. The goal of learning protocols is to have a performer maintain a sufficient level of motivation to perform the task and ultimately transfer the acquired (learned) skill or materials to a novel situation or environment. RNE informs us about learning efficiency within a CI paradigm. Within a CI paradigm, one would predict that RNE would be lower (e.g., in the low efficiency quadrant) for the RND group than the BLK group during acquisition. This relationship should reverse during retention and transfer, with the RND group showing higher efficiency values than the BLK group. RNI provides a measure of motivation regarding the learning of the tasks. This index of involvement may provide some insight regarding the learning paradox of contextual interference. For example, during the acquisition phase, the BLK group may initially be more engaged in the task because they experience success with their performance.

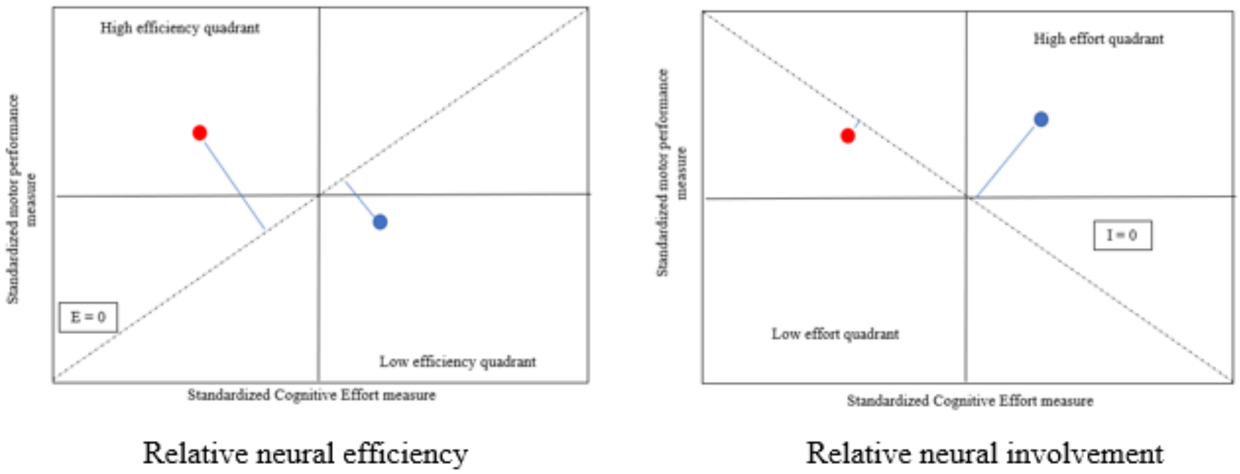

Figure 4. Hypothetical graphs of a) relative neural efficiency and b) relative neural involvement during a retention test. In both examples, the red dot represents random practice and the blue dot represents blocked practice. On the left, random practice has resulted in higher performance scores with lower cognitive effort as compared to the blocked practice, leading to an RNE value within the high efficiency quadrant. On the right, both random and blocked conditions perform similarly; however, the blocked practice results in higher RNI, suggesting higher cognitive effort in order to achieve the same performance. Those training in a random protocol may have RNE values in the high efficiency quadrant, whereas those training in a blocked protocol may have RNI in the high effort quadrant.

CALCULATING RELATIVE NEURAL EFFICIENCY AND INVOLVEMENT

For the relative neural efficiency and relative neural involvement metrics using fNIRS data, any of the four biomarkers can be used (e.g., total hemoglobin (ΔHbT)) along with meaningful behavioral performance measures (e.g., maze distance (MD) for a computer maze task). RNE metrics calculations are based on the details in Shewokis et al[12] in which she used the normalized change in oxygenated hemoglobin (ΔHbO) representing quantitative cognitive effort and normalized global score representing performance (Figure 5). RNI calculations are based on applications with subjective effort and instructional motivation by Paas[34] and colleagues and represented in an fNIRS application with a search and surveillance task using a high-fidelity training simulator for unmanned aircraft with normalized behavioral performance measures and normalized oxyhemoglobin and deoxyhemoglobin measures[39]. RNE represents the perpendicular distance of the standardized performance score relative to the standardized cognitive effort scores (see equations 1 and 2). Then RNE and RNI (see equation 3) can be plotted as cartesian coordinates for each participant, trial and maze for the retention and transfer phases.

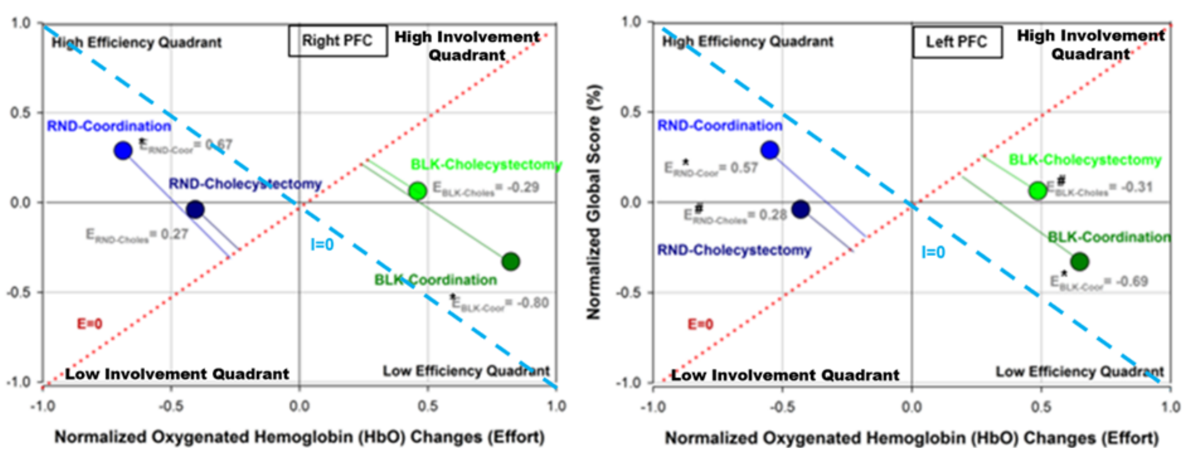

Figure 5. Relative neural efficiency and relative neural involvement in the left and right prefrontal cortex following random (blue) and blocked (green) surgical simulation protocols. Those participants who trained using random protocol had higher RNE within the high efficiency quadrant, whereas those in the blocked protocol had lower RNE within the low efficiency quadrant[26]. Blocked trained participants had higher RNI for the more difficult transfer task of a simulated cholecystectomy and is located in the high involvement quadrant while participants who had the random training elicited lower RNI scores and were in the low involvement quadrant.

$$P_z = \frac{\frac{1}{MD_i} - \frac{1}{MD_{GM}}}{\frac{1}{MD_{SD}}} \tag{1}$$

$$CE_z = \frac{\frac{1}{\Delta HbT_i} - \frac{1}{\Delta HbT_{GM}}}{\frac{1}{\Delta HbT_{SD}}} \tag{2}$$

$$RNE = \frac{P_z - CE_z}{\sqrt{2}} \qquad RNI = \frac{P_z + CE_z}{\sqrt{2}} \tag{3}$$

LATERALIZATION INDEX

Another useful measure that can be used to understand the contextual interference effect is the lateralization index[40,41]. The lateralization index can be used to explore lateralization between the two hemispheres of the cerebral cortex.

Laterality indices (LI) can be described and calculated for continuous wave fNIRS measurements. The calculation may involve a specific set of optodes or regions of interest as well as the identification and specification of a feature of interest of the fNIRS biomarkers. Izzetoglu[41] used the maximum values of the two channels representing the left PFC and the maximum values for two channels representing the right PFC.

WHAT THE LATERALIZATION INDEX TELLS US

The lateralization index provides us with information regarding the strength of activation of the region of interest or hemisphere of action. In the schematic below, depicted are the regions of interest in the prefrontal cortex along with the associated functions. This information allows for a more detailed interpretation of the task selection and meaning of the results of the analyses. For example, in Izzetoglu and colleagues[41], laterality indices were calculated for the acute mediation tasks for oxyhemoglobin and deoxyhemoglobin. Findings showed that acute meditation reflects a move toward left frontal lateralization.

Typically, lateralization indices are reported in table, line graph or box plot formats. To facilitate understanding and simultaneous interpretation of the lateralization index, we created a unique graph applying the data visualization benefits of Likert (divergent stacked bar) plots superimposed on a topographical map of the prefrontal cortex (see Figure 6). Positive scores indicate a left lateralization (see the blue shadings) while negative scores are represented as the red shadings. The neutral zone represents lateralization indices from -0.09 to 0.09 or close to the zero line. As well, we included horizontal box plots of the blocked and random groups of the peak HbT (see Figure 7) which is comparable to the hypothetical distribution in Figure 6.

EXAMPLE

In the protocol investigating the effects of contextual interference when learning simulated surgical tasks across acquisition, retention, and transfer phases, Shewokis and colleagues[12,13] analyzed one of the biomarkers (peak ΔHbT) for all 11 participants during performance of the coordination simulated surgical transfer task. The behavioral measure, global score, represents a composite score of accuracy, time, and skill execution it ranges from 0-100%. The normalized peak ΔHbT provides some information about the localized cerebral blood flow changes. A post-hoc analysis of the peak ΔHbT for the simulated coordination surgical task transfer was calculated. The peak left hemisphere of the PFC (optodes 1-8) and right hemisphere (optodes 9-16) for the peak ΔHbT biomarker for the coordination transfer task. For the RNE measures, both the right and left PFC RNE measures were significant [$t(9) = -3.837$, $p=0.004$, Hedges $g = 0.826$ and $t(9) = -1.285$, $p=0.045$, Hedges $g = 0.666$], respectively. RND groups resulted in positive, less variable [M $\pm$SD: 0.518 $\pm$ 0.393; 0.413 $\pm$ 0.542] RNE scores than BLK [M $\pm$SD: -0.622 $\pm$ 0.590; -0.496 $\pm$ 0.413] for the right and left frontal hemispheres, respectively. No differences were detected for the RNI measures with [$t(9)< 1.0$, $p= 0.703$ and 0.986] for the right and left frontal hemispheres, respectively. We then calculated the LI for all participants for each trial. An independent samples t-test resulted in $t(31)$ 2.112, $p = 0.043$ (2-tailed) with Hedge's $g = 0.723$ (95% Confidence Interval : -1.442, -0.023; Prediction Interval: 3.38, -1.94). Interestingly, the BLK group showed a more right frontal lateralization (mean ± SD; LI = -0.711±1.696) while the RND group was more left frontally lateralized (LI: 0.246 ±0.837). For this virtual reality simulated task, the BLK group focused more on the visuomotor attentional components while RND was more oriented to the goal orientation, learning and memory processes.

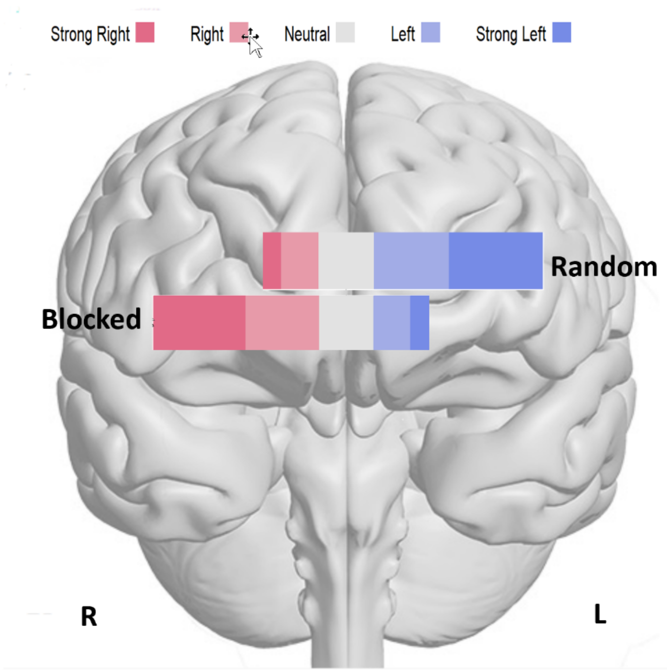

Figure 6. Hypothetical Lateralization Index as divergent stacked bar (Likert) charts. The random group demonstrates a strong left lateralization (dark blue) whereas the blocked group demonstrates a strong right lateralization (dark red).

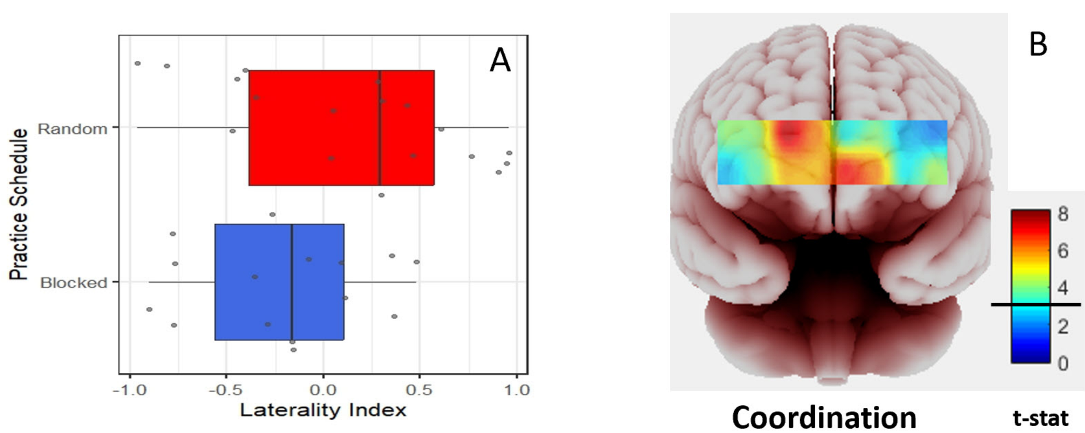

Figure 7. Horizontal box plot from blocked and random groups after training on simulated laparoscopic surgery tasks[13,26]. The top, red box plot is the random group and the bottom, blue box plot is the blocked group (A). Topographical map (B) with t-test contrasts comparing the blocked and random groups for the coordination transfer task. The critical t-value is [$t(9) = 2.262$, $p < 0.05$, two-tailed] with the colored bar indicating regions of statistical significance where teal through dark red colors represent significant differences between blocked and random groups for total hemoglobin (μmolar). Contrasts represent average blocked – random differences.

CALCULATING LATERALITY INDICES

The number of channels used to calculate a laterality index is dependent upon the research design and the goals of the research. Laterality indices were calculated using Equation (5) for oxygenated, de-oxygenated and total hemoglobin biomarkers for the right and left

PFCs which resulted in the average of channels 9-16 and 1-8, respectively.. The laterality index (LI) ranges from -1 to +1. A positive LI represented that the person was left lateralized and a negative LI registered the person as right lateralized.

$$Laterality\ Index\ = \frac{((fe_i\, biomk_j\_L) - ((fe_i\, biomk_j\_R)))}{(fe_i\, biomk_j\_L + ((fe_i\, biomk_j\_R)))}$$

Where fe_i = feature of interest (e.g., maximum, mean, median, standard deviation, and so forth); i = 1… n; $biomk_j$ = biomarker of interest (oxygenated hemoglobin, de-oxygenated hemoglobin, total hemoglobin, and oxygenation); j = 1 to 4; L = left region of interest or channel; R = right region of interest or channel.

Implementation of the laterality index for various tasks and practice organization methods may provide important information and insights for the design of future learning protocols.

SUMMARY AND CONCLUSIONS

In 1966, Batting[1,4] identified the Contextual Interference effect, which highlighted the importance of conditions of practice during the time in which individuals initially learn a skill. The contextual interference (CI) effect occurred when learners experience interference during the acquisition phase; this has a negative effect on early performance but a positive effect on skill learning. Within the field of motor learning, researchers have studied CI for more than 40 years by primarily focusing on performance outcomes within an experimental paradigm where learners are initially presented with practice trials in a randomized (high CI) or blocked (low CI) order. With the advent of more accessible brain imaging techniques such as fMRI, EEG, and fNIR, researchers have begun to unpack what is occurring in the brain that is driving the CI effect. In particular, the use of fNIRs has allowed researchers to study prefrontal cortex activity as learners actively engage in motor and cognitive tasks. In this paper, we describe three useful tools that leverage fNIRs measures of oxyhemoglobin in different ways to better understand the prefrontal cortex changes within a CI research paradigm. Two of these measures, relative neural efficiency and relative neural involvement, stem from Cognitive load theory and allow for the examination of behavioral performance measures within the context of PFC activity. Relative neural efficiency (RNE) looks at the relationship between cognitive effort and performance; within a CI paradigm, individuals experiencing high CI should initially have low RNE (indicating high effort with low performance) with an eventual shift to high RNE (indicating low effort with high performance). Relative neural involvement, on the other hand, provides a measure of participant engagement and motivation using a combination of cognitive effort with performance output. Finally, the lateralization index provides a measure of the strength of activation within a region of the PFC. All three measures provide novel ways in which researchers can uncover the underpinnings of the contextual interference effect.

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