ABSTRACT

Title of Dissertation: INVESTIGATIONS TO UNDERSTAND THE UNDERLYING BRAIN PROCESSES WHICH ENHANCE COGNITIVE-MOTOR LEARNING AND PERFORMANCE

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The ability to effectively and efficiently process task-relevant information is a critical element to a wide range of cognitive-motor activities. Indeed, various studies have illustrated that elite performers exhibit more refined neuro-cognitive processes than novices. However, it is unclear how these neuro-cognitive information processing abilities develop as skill is acquired. In this dissertation, I provide some evidence to address this gap in the literature. Study 1, entitled “Empirical evidence for the relationship between cognitive workload and attentional reserve” (Jaquess et al., 2017), provided evidence illustrating the relationship between mental workload and attentional reserve. Study 2, entitled “Changes in mental workload and motor performance throughout multiple practice sessions under various levels of task difficulty”, builds from the knowledge gained from Study 1 and extends it to a cognitive-motor learning/practice context over the course of four days. Finally, Study

3, entitled “How engaged are you? An investigation of the neurocognitive mechanisms of self-controlled practice during cognitive-motor learning”, was built upon the knowledge gained from Study 2 to further investigate how aspects of the practice environment, specifically the aspect of control, impact cognitive load and learning outcomes. Broadly, these studies illustrate how some of the neuro-cognitive processes related to information processing in cognitive-motor skills, specifically elements of the electroencephalogram (EEG), change with learning and the acquisition of skill.

INVESTIGATIONS TO UNDERSTAND THE UNDERLYING BRAIN PROCESSES WHICH ENHANCE COGNITIVE-MOTOR LEARNING AND PERFORMANCE

by

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Chapter 1: General Introduction

The ability to effectively and efficiently process task-relevant information is a critical element to a wide range of cognitive-motor activities. Indeed, various studies have illustrated that elite performers exhibit more refined cognitive processes than novices. For example, high-level performers tend to ignore task-irrelevant information (Haider & Frensch, 1999), more efficiently process task-relevant information (Furley, Memmert, & Schmid, 2013; Jarodzka, Scheiter, Gerjets, & Van Gog, 2010), and display more refined brain activation (Costanzo et al., 2016; Deeny, Haufler, Saffer, & Hatfield, 2009; Haufler, Spalding, Santa Maria, & Hatfield, 2000) than less-skilled performers. Various theories of learning make efforts to describe how such characteristics develop. Notably, Cognitive Load Theory (CLT) proposes that as skills are learned, schemas, which are cognitive structures that store and organize information, are developed in such a way that increasingly complex and interconnected pieces of knowledge can be represented by a limited number of schemas, reducing the cognitive load, or mental workload, of the learner/performer (Schmidt, 1975; Van Merrienboer & Sweller, 2005).

If the neuro-cognitive aspects of cognitive-motor behavior are so vital to performance, then it is of importance to assess such factors accurately. Of note, various elements of the electroencephalogram (EEG) have been linked with processes that are relevant to information processing. For example, in the frequency domain, alpha band power has been linked to attention, inhibitory processes, long-term memory, and arousal (Hanslmayr et al., 2005; Klimesch, 1999; Klimesch, Sauseng, &

Hanslmayr, 2007; Ray & Cole, 1985), while theta band power has been linked with working memory engagement (Doppelmayr, Finkenzeller, & Sauseng, 2008; Sauseng, Klimesch, Schabus, & Doppelmayr, 2005). The following studies that comprise the present program of research employ these indicators, among others, to assess aspects of information processing related to the quality of cognitive-motor performance.

Study 1, entitled "Empirical evidence for the relationship between cognitive workload and attentional reserve" (Jaquess et al., 2017), provided evidence illustrating the relationship between mental workload and attentional reserve. Various theoretical accounts (Broadbent, 1957; Kahneman, 1973; Kantowitz, 1987; Sanders, 1979; Wickens, 2002) have described these two concepts as being inversely related, but empirical work conducted to investigate this claim was lacking. The initial study reported in this document utilized specific derivatives of the electroencephalogram to assess both mental workload and attentional reserve. Spectral power derived from the EEG time series that indexed cortical activation was used to assess mental workload (Gentili et al., 2018; Gevins & Smith, 2003; Rietschel et al., 2012), while the amplitudes of specific components of the event-related potential in response to the presentation of unattended "novel" sounds were used to assess attentional reserve (Miller, Rietschel, McDonald, & Hatfield, 2011; Rietschel et al., 2014). The relationship between these two families of measures was assessed using canonical correlation in order to assess the directionality of the relationship.

Study 2, entitled "Changes in mental workload and motor performance throughout multiple practice sessions under various levels of task difficulty", builds from the knowledge gained from Study 1 and extends it to a cognitive-motor learning/practice context. While mental workload has been investigated during performance, a limited body of work has examined it dynamically during cognitive-motor learning, while none have done so over multiple sessions while concurrently assessing it at varying levels of task difficulty. In accord with complementary learning frameworks, including cognitive load theory (Sweller, 1988, 2010) and the challenge point framework (Guadagnoli & Lee, 2004) it is reasonable to expect that the level of difficulty at which a skill is practiced would impact not only the rate of skill acquisition, but also the rate at which mental workload reduces due to learning (i.e., relatively slowed for more challenging tasks compared to an easy task). Thus, Study 2 aimed to monitor specific elements of mental workload through cortical dynamics using EEG during a task practiced under two levels of difficulty over four days.

Finally, Study 3, entitled “How engaged are you? An investigation of the neurocognitive mechanisms of self-controlled practice during cognitive-motor learning”, was built upon the knowledge gained from Study 2 to further investigate how aspects of the practice environment, specifically the aspect of control, impact cognitive load and learning outcomes. Previous research indicates that self-controlled practice can be a more effective approach than externally-controlled practice. This effect may be due, in part, to increased neurocognitive engagement during self-controlled practice relative to externally-controlled practice (Wulf, 2007). Study 3 was conducted to investigate this notion using electroencephalographic (EEG) measures of related to mental workload, memory system engagement (i.e., working memory and long-term memory), and attention. Thirty-two novice participants were divided into two groups, based on the presence and absence of control, to practice a golf putting task over the course of three days. EEG measures, representative of working memory (theta power) and central executive engagement (fronto-parietal theta coherence), as well as attention and long-term memory engagement (alpha 2 power) were collected throughout the experiment. It was hypothesized that self-controlled practice would elevate working memory engagement and facilitate refinement of long-term memory processing and attention, resulting in relative performance improvement compared to the absence of such control.

The program of research, centered around the concepts of information processing during cognitive motor learning and performance, is organized sequentially beginning with Study 1 and progressing to Study 3, along with a general discussion of the conclusions which can be drawn from them.

References

Broadbent, D. E. (1957). A mechanical model for human attention and immediate memory. Psychological Review, 64(3), 205.

Costanzo, M. E., VanMeter, J. W., Janelle, C. M., Braun, A., Miller, M. W., Oldham, J., . . . Hatfield, B. D. (2016). Neural efficiency in expert cognitive-motor performers during affective challenge. Journal of Motor Behavior, 48(6), 573-588.

Deeny, S. P., Haufler, A. J., Saffer, M., & Hatfield, B. D. (2009). Electroencephalographic coherence during visuomotor performance: a comparison of cortico-cortical communication in experts and novices. Journal of Motor Behavior, 41(2), 106-116.

Doppelmayr, M., Finkenzeller, T., & Sauseng, P. (2008). Frontal midline theta in the pre-shot phase of rifle shooting: differences between experts and novices. Neuropsychologia, 46(5), 1463-1467.

Furley, P., Memmert, D., & Schmid, S. (2013). Perceptual load in sport and the heuristic value of the perceptual load paradigm in examining expertise-related perceptual-cognitive adaptations. Cognitive Processing, 14(1), 31-42.

Gentili, R. J., Jaquess, K. J., Shuggi, I. M., Shaw, E. P., Oh, H., Lo, L. C., . . . Hatfield, B. D. (2018). Combined assessment of attentional reserve and cognitive-motor effort under various levels of challenge with a dry EEG system. Psychophysiology.

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. Theoretical Issues in

Ergonomics Science, 4(1-2), 113-131.

Guadagnoli, M. A., & Lee, T. D. (2004). Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. Journal of Motor Behavior, 36(2), 212-224.

Haider, H., & Frensch, P. A. (1999). Eye movement during skill acquisition: More evidence for the information-reduction hypothesis. Journal of Experimental Psychology: Learning, Memory, and Cognition, 25(1), 172.

Hanslmayr, S., Klimesch, W., Sauseng, P., Gruber, W., Doppelmayr, M., Freunberger, R., & Pecherstorfer, T. (2005). Visual discrimination performance is related to decreased alpha amplitude but increased phase locking. Neuroscience Letters, 375(1), 64-68.

Haufler, A. J., Spalding, T. W., Santa Maria, D., & Hatfield, B. D. (2000). Neuro-cognitive activity during a self-paced visuospatial task: comparative EEG profiles in marksmen and novice shooters. Biological Psychology, 53(2), 131-160.

Jaquess, K. J., Gentili, R. J., Lo, L. C., Oh, H., Zhang, J., Rietschel, J. C., . . . Hatfield, B. D. (2017). Empirical evidence for the relationship between cognitive workload and attentional reserve. International Journal of Psychophysiology, 121, 46-55. doi: https://doi.org/10.1016/j.ijpsycho.2017.09.007

Jarodzka, H., Scheiter, K., Gerjets, P., & Van Gog, T. (2010). In the eyes of the beholder: How experts and novices interpret dynamic stimuli. Learning and Instruction, 20(2), 146-154.

Kahneman, D. (1973). Attention and effort: Citeseer.

Kantowitz, B. H. (1987). 3. Mental Workload. Advances in Psychology, 47, 81-121.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Research Reviews, 29(2–3), 169-195. doi: http://dx.doi.org/10.1016/S0165-0173(98)00056-3

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: the inhibition–timing hypothesis. Brain Research Reviews, 53(1), 63-88.

Miller, M. W., Rietschel, J. C., McDonald, C. G., & Hatfield, B. D. (2011). A novel approach to the physiological measurement of mental workload. International Journal of Psychophysiology, 80(1), 75-78. doi: http://dx.doi.org/10.1016/j.ijpsycho.2011.02.003

Ray, W. J., & Cole, H. W. (1985). EEG alpha activity reflects attentional demands, and beta activity reflects emotional and cognitive processes. Science, 228, 750-752.

Rietschel, J. C., McDonald, C. G., Goodman, R. N., Miller, M. W., Jones-Lush, L. M., Wittenberg, G. F., & Hatfield, B. D. (2014). Psychophysiological support of increasing attentional reserve during the development of a motor skill. Biological Psychology, 103, 349-356.

Rietschel, J. C., Miller, M. W., Gentili, R. J., Goodman, R. N., McDonald, C. G., & Hatfield, B. D. (2012). Cerebral-cortical networking and activation increase as a function of cognitive-motor task difficulty. Biological Psychology, 90(2), 127-133. doi: http://dx.doi.org/10.1016/j.biopsycho.2012.02.022

Sanders, A. F. (1979). Some remarks on mental load Mental workload (pp. 41-77):

Springer.

Sauseng, P., Klimesch, W., Schabus, M., & Doppelmayr, M. (2005). Fronto-parietal EEG coherence in theta and upper alpha reflect central executive functions of working memory. International Journal of Psychophysiology, 57(2), 97-103.

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. Psychological Review, 82(4), 225

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12(2), 257-285. doi: http://dx.doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2010). Element Interactivity and Intrinsic, Extraneous, and Germane Cognitive Load. Educational Psychology Review, 22(2), 123-138. doi: 10.1007/s10648-010-9128-5

Van Merrienboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. Educational Psychology Review, 17(2), 147-177.

Wickens, C. D. (2002). Multiple resources and performance prediction. Theoretical Issues in Ergonomics Science, 3(2), 159-177.

Wulf, G. (2007). Self-controlled practice enhances motor learning: implications for physiotherapy. Physiotherapy, 93(2), 96-101.

Chapter 2: Empirical Evidence for the Relationship between Cognitive Workload and Attentional Reserve

Abstract

While the concepts of cognitive workload and attentional reserve have been thought to have an inverse relationship for some time, such a relationship has never been empirically tested. This was the purpose of the present study. Aspects of the electroencephalogram were used to assess both cognitive workload and attentional reserve. Specifically, spectral measures of cortical activation were used to assess cognitive workload, while amplitudes of the event-related potential from the presentation of unattended "novel" sounds were used to assess attentional reserve. The relationship between these two families of measures was assessed using canonical correlation. Twenty-seven participants performed a flight simulator task under three levels of challenge. Verification of manipulation was performed using self-report measures of task demand, objective task performance, and heart rate variability using electrocardiography. Results revealed a strong, negative relationship between the spectral measures of cortical activation, believed to be representative of cognitive workload, and ERP amplitudes, believed to be representative of attentional reserve. This finding provides support for the theoretical and intuitive notion that cognitive workload and attentional reserve are inversely related. The practical implications of this result include improved state classification using advanced machine learning techniques, enhanced personnel selection/recruitment/placement, and augmented learning/training.

Introduction

The concept of mental workload has been long discussed in cognitive psychology. Broadbent (1957) was among the first to discuss the notion that cognitive resources are limited and that a given operation consumes a portion of those resources. Broadbent and others (Kahneman, 1973; Kantowitz, 1987; Sanders, 1979; Wickens, 2002) used this notion of limited cognitive capacity to explain that humans are able to effectively perform tasks that do not completely consume these cognitive resources. In other words, tasks can be successfully performed when there is some capacity in reserve. In the event that the demands of the cognitive system exceed its capacity, a situation of cognitive "overload" emerges and task failure is much more likely to occur.

In a society with ever-increasing informational demands, there is a growing requirement to manage the demand on one's mental systems (i.e., mental workload) in an adaptive manner so as to maximize productivity and performance. This is especially true of tasks with relatively high cognitive demand, such as aviation. As a result, investigators have made efforts to measure and monitor mental workload using a variety of measurement methodologies. For example, the NASA Task Load Index (TLX), a self-report measure, has been shown to be a valid and reliable indicator of workload (Hart & Staveland, 1988) and is widely used (see (Hart, 2006) for a review). Heart rate variability (HRV) has also been shown to be indicative of mental workload (Cinaz, Arnrich, La Marca, & Tröster, 2013; Mehler, Reimer, & Wang, 2011). Specifically, the root mean square of successive differences (RMSSD) measure of HRV, thought to be reflective of parasympathetic activation, has been found to have significant negative relationships with workload, even during short periods of measurement (Chang & Lin, 2005; Munoz et al., 2015; Thong, Li, McNames, Aboy, & Goldstein, 2003). Lastly, Gevins and Smith (2003) have noted that electroencephalography (EEG) is a useful tool in the measurement of mental workload due to its sensitivity to attention and alertness levels via various indicators of cortical activation. Indeed, many investigators have used EEG to measure mental workload with success. Gevins and Smith (2003) showed that both theta (5-7 Hz) and alpha band (8-12 Hz) EEG activity have notable relationships with mental workload. Hankins and Wilson (1998) also observed that, during the performance of several real-life flight tasks, as task demand increased, alpha power decreased and theta power increased. An experiment by Rietschel et al. (2012) revealed that task difficulty had positive relationships with frontal theta (3-8 Hz) and occipital beta (13-30 Hz) and gamma (30-44 Hz) power and a negative relationship with high alpha (10-13 Hz) power at central and parietal sites. Lastly, several research groups (Gentili et al., Submitted; Hockey, Nickel, Roberts, & Roberts, 2009; Nassef et al., 2009; Postma, Schellekens, Hanson, & Hoogeboom, 2005) have observed that a ratio between theta and alpha at various midline electrode sites is indicative of mental workload. These findings show that EEG frequency-domain measures of cortical activation have strong relationships with mental workload.

Within the domain of EEG, time-domain measures in the form of event-related potentials (ERPs) have also been related to task demands. Using a randomized sequence of novel sounds playing in the auditory background of a primary visuomotor task (Tetris ®) to generate ERPs, Miller, Rietschel, McDonald, and Hatfield (2011) found that various ERP components, including the N1, the P2, and the P3a, or the "novelty P3" (Polich, 2007), components (all maximal at Cz), shared a negative relationship with task demand, such that as task demand increased, ERP amplitudes reduced. By using these novel, to-be-ignored auditory stimuli as probes of cognitive/attentional resources while participants are engaged in a primary task, it was argued by Miller and colleagues that the stimuli engaged resources beyond those demanded by the primary task, thereby engaging the "spare capacity" described by previous investigators (Kahneman, 1973; Kantowitz, 1987; Wickens, 2002). This spare capacity has been labelled by Miller and colleagues (Miller et al., 2011; Rietschel et al., 2014) as "attentional reserve". How much of this attentional reserve the novel sounds capture, then, may depend upon how much reserve remains during the performance of the primary task. In the context of Miller et al. (2011), as primary task demand increased, less attentional reserve was available to process the novel auditory stimuli, resulting in a decrease in ERP amplitudes.

The studies discussed collectively suggest a simple, yet noteworthy, relationship between mental workload and attentional reserve. As task demands increase, mental workload increases while attentional reserve decreases. In the present viewpoint, the ERP can be interpreted as being indicative of attentional reserve, while the EEG spectral measures of cortical activation, alongside the NASA TLX and HRV, can be interpreted as being indicative of mental workload. Thus, the amplitudes of the ERP, as a measure of attentional reserve, should consistently exhibit inverse relationships with measures of mental workload, with a present focus on EEG spectral measures of cortical activation.

While it is theoretically and conceptually understood that mental workload and attentional reserve are inversely related, to our knowledge the two concepts have not been explicitly contrasted in an empirical study to illustrate this inverse relationship. One experiment by (Brouwer et al., 2012) did collect both spectral and ERP data simultaneously for the purposes of measuring workload, but the two indicators were not compared in a way that elucidates what aspect of cognitive capacity they represent. Therefore, the aim of the present study is to fill this gap in the literature. Using the visuo-motor task of operating a flight simulator under varying degrees of challenge, and employing the ERP technique used by Miller and colleagues (Miller et al., 2011; Rietschel et al., 2014), we assessed both frequency- and time-domain EEG measures to illustrate the theoretical relationship between mental workload and attentional reserve. We also collected self-report and HRV indicators of task demand to provide confidence in the experimental manipulation.

It is hypothesized that EEG spectral measures of cortical activation, taken as a measure of mental workload, will have an overall positive relationship with task difficulty. To ensure that all measures of EEG spectral power reflect cortical activation in a directionally unified fashion for purposes of clarity and simplicity, alpha power values, which typically have a negative relationship with mental workload, will be multiplied by (-1). In regards to the ERP as a measure of attentional reserve, it is hypothesized that ERP amplitudes will show a negative relationship with task difficulty as a result of fewer attentional resources being available to process the novel sounds. Furthermore, and most importantly, it is predicted that EEG spectral measures of workload and ERP measures of attentional reserve will have a negative relationship with each other. As a manipulation check of task demand, self-report scores (NASA TLX and Visual Analog Scales) and HRV information were gathered alongside the EEG data. We predict that NASA TLX indicators of workload will increase with task demand, while HRV, specifically RMSSD as an indicator of parasympathetic activation, will reduce as task demand increases.

Methods

Participants

Sixty-three (63) healthy participants (seven females) between the ages of 19 and 26 years performed the visuo-motor task of operating a flight simulator at the United States Naval Academy (USNA) using Prepar3D® software (version 1.4, Lockheed Martin Corporation) under three levels of challenge. Of these, 27 participants, all of whom were males, had usable data from both spectral and ERP measures simultaneously. All participants were part of the powered flight program at the USNA, during which participants were expected to perform a successful solo-flight in a small single engine propeller plane upon the completion of the program; all participants had an active interest in becoming pilots. This study was approved by the local institutional review board and written informed consent was obtained from all participants.

Task Description

Three scenarios of varying task demand, or “challenge”, were selected from predefined flight training challenges with minor updates and developed with advice from experienced pilots. In each scenario, participants were asked to control a simulated aircraft (T-6A Texan II SP2 USN) with the control stick, throttle, and rudder pedals. The flight was programmed to begin at 0900 virtual time, at N38.5400° latitude and W77.0200° longitude (around Washington, DC, USA), at an altitude of 4000 feet. Each scenario was composed of a 1-min setup period followed by a 10-min flight scenario. The three scenarios (S1, S2 and S3) were defined as follows:

a) S1 ("Easy"): The goal was to maintain the aircraft's current altitude (4000 ft), heading (180°), and airspeed (180 knots) while maintaining such a straight and level course. The weather was defined by no clouds, precipitation, or wind with unlimited visibility.

b) S2 ("Medium"): The goal was to maintain the aircraft's current heading (180°), airspeed (180 knots), and a "wings-level" attitude while continuously making assigned altitude changes (between 4000 and 3000 feet) with ascent and descent rates of 1000 feet per min. The weather was defined by heavy clouds (1/16 mi or 0.1 km of visibility), but no precipitation and no wind.

c) S3 ("Hard"): The goal was to maintain the aircraft's current airspeed (180 knots), while adjusting both heading and altitude. Heading changes consisted of both left (180° to 090°) and right (090° to 180°) turns maintaining a 15° angle of bank. Altitude changes occurred during turns such that participants descended while turning left and ascended while turning right at a rate of 1000 feet per min. The weather was defined by heavy clouds (1/16 mi or 0.1 km of visibility) and a moderate (16 knots) easterly wind, but no precipitation.

As part of an exploratory investigation to assess potential behavioral indicators of attentional reserve, one unexpected or "surprise" event, a flashing "Master Warning" light, occurred from 7 min and 31 s to 7 min and 33 s in each scenario. After the completion of all three scenarios, the participant's detection of this event was assessed, retrospectively.

Scenario sequence was counter-balanced. Novel sounds were generated in a similar way as reported in Miller et al. (2011) using stimuli initially assembled by Fabiani, Kazmerski, Cycowicz, and Friedman (1996), while using "ear-bud" speakers in place of external computer speakers.

Procedure

Upon arrival, the participant provided informed consent upon receiving a general explanation of the task. A handedness survey was also administered. Participants were then allowed to familiarize themselves with the flight simulator and the novel sounds for 5 min. Upon completion of the familiarization session, the experimenters prepared the participants for fitment of the EEG cap and ECG sensor. Participants were assigned an initial challenge and provided with relevant instructions. Each participant was provided 1 min to stabilize the plane on the starting parameters of the scenario. After this setup period, the first 10 min scenario, complete with the novel sound stimuli, was executed. Upon completion, participants were provided the Visual Analog Scales (VAS) and National Aeronautics and Space Administration (NASA) Task Load Index (TLX) surveys to report their subjective experience upon completion of the scenario. The same order of procedures was followed until all three challenge levels were completed.

Participants were then disconnected from the equipment, debriefed about the purpose of the experiment, thanked, and excused.

Data Acquisition

Self-report

Two separate self-report measures were used to assess subjective feelings related to task performance: Visual Analog Scales (Appendix A.) and the NASA TLX (Appendix B.). Five visual analog scale questions were posed: (1) Overwhelmed: How overwhelmed was I by the task? (0 = not at all, 100 = completely overwhelmed); (2) Concentration: How much did I have to concentrate to perform the task? (0 = little, 100 = high); (3) Mental Load: How mentally loaded did I feel while performing the task? (0 = not loaded, 100 = completely loaded); (4) Ease: How easy was the task? (0 = extremely easy, 100 = not easy at all/hard); (5) Tiredness: How tired was I after the task? (0 = not tired, 100 = very tired).

The six subscales of the NASA TLX indexed mental demand, physical demand, temporal demand, performance, effort, and frustration. Each subscale provided ranges from 0 to 100 with higher scores reflecting greater demands and performance failures.

Performance

A custom plug-in logging program continuously recorded all of the relevant indicators of performance during flight simulation with a sampling rate of 2 Hz. In particular, the four metrics of airspeed, altitude, heading, and vertical speed were selected due to their relevance and sensitivity to the quality of the pilot’s performance.

EEG and ECG

Both EEG and ECG were collected via g.tec data collection hardware (g.tec medical engineering GmbH, Austria). EEG was collected using dry g.sahara sensors from four sites along the frontal (Fz), fronto-central (FCz) central (Cz), and parietal (Pz) midline . ECG was collected with pre-gelled disposable Ag/AgCl sensors from a unipolar placement on the below the bottom left rib. Both EEG and ECG were amplified using the same g.USBamp amplifier and electrode impedances were maintained below 5 kOhm. Data sampling rate was 512 Hz. The right mastoid was employed as the ground for the system and the left ear (A1) was used as the online reference. Data from the right ear (A2) was also recorded for later re-referencing purposes. Lastly, an online band-pass filter was applied with a range of 0.01 Hz to 40 Hz.

Surprise element

Surprise data were collected at the conclusion of all three scenarios for each participant. Participants were told that throughout the scenarios, some lights lit up on the instrument panel. Participants were then asked if they saw any, to point to the one that they saw, and identify the scenarios in which they detected the stimulus. Indication of the correct warning light (Master Warning) for a given scenario was marked as detection of the surprise and yielded a score of “1”. Failure yielded a score of “0” for that scenario.

Data Processing

Performance

In each scenario, acceptable performance was achieved by maintaining flight parameters (e.g., altitude, airspeed, heading, bank angle, etc.) within tolerance limits of the goal as specified by experienced pilots. The criteria were defined as follows:

a) S1 (low demand): no more than ±200 feet from specified altitude, ±10 knots from specified airspeed, ±5° from specified heading, and ±5° from specified bank angle, respectively.

b) S2 (moderate demand): no more than ±200 feet of assigned altitude at each moment, ±10 knots of specified airspeed, ±5° of specified heading, and ±5° of specified bank angle, ±500 feet per min of specified ascent and descent rates, respectively.

c) S3 (high demand): no more than ±200 feet of assigned altitude at each moment, ±10 knots of specified airspeed, ±5° of assigned heading at each moment, and ±5° of specified angle of bank, ±500 feet per min of specified ascent and descent rates, respectively.

The deviations of each flight parameter were bounded above and below the aforementioned decision boundaries, and then for each metric the average performance per min was calculated by subtracting the area under the bounded deviation curve from the area of the decision boundary once per min. Moreover, to reflect the dynamic quality on the average performance measurement, for each flight parameter, the average performance gain was computed per min as the difference between two values, which were the sum of the directional derivatives of a flight parameter and the sum of the maximum directional derivatives of the same parameter assuming the worst. Each average performance gain adjusted the corresponding average performance so that it could differentiate two average performance values even if their areas under the bounded deviation curves were same. The gained average performance values were normalized to be ranged between 0 and 1, where greater values indicate better performance. Lastly, a composite performance index was obtained using the weighted $\ell 2$-norm of a vector defined by the selected performance metrics with the number of metrics as the weight. In particular, the selected performance metrics were different in each scenario because of various required conditions in each level of challenge; for instance, all four metrics, three metrics except altitude, and two of them (airspeed and vertical speed) were considered for S1, S2, and S3, respectively.

ECG - HRV

Peaks of the R-wave of the standard PQRST wave complex within the ECG signal were detected using a custom Matlab code (The Mathworks Inc., USA) and inter-beat-interval (IBI) was then extracted from the middle 5 min (300 s) of the 10 min signal. Finally, the mean squared differences before and after each interval were calculated and then the square root value was taken to extract the RMSSD value.

EEG - Spectral measures

The data were re-referenced to an averaged-ears montage and then processed by employing an IIR filter with a 50-Hz low-pass setting, 48 dB roll-off. Next, the data were segmented into 1 s epochs and mean baseline-corrected (1-1000 ms). All epochs were then visually inspected and those containing significant artifact were removed from further analysis. Next, a Fast Fourier transform was implemented using a Hamming window with 50% overlap; 1-Hz resolution was obtained. Finally, the spectral data were averaged within three two-minute periods (0-2 min, 4-6 min, 8-

10 min) to characterize the brain activity during the early, middle, and late stages of each scenario. Finally, the frequency bins were log-transformed and summed to obtain spectral power for the functional bandwidths of interest: Theta (3-8 Hz), Low-Alpha (8-10 Hz), High-Alpha (10-13 Hz), Broadband Alpha (8-13Hz), Beta (13-30 Hz).

EEG - ERP

The data were re-referenced to an averaged ears montage and then were processed by employing an IIR filter with a 20 Hz low-pass setting, 48 dB roll-off. Next, 1 s epochs that were time-locked to the novel sound stimuli were extracted from the time series. These epochs were mean baseline-corrected using the pre-stimulus interval (i.e. -100 – 0 ms). The transformed data were then visually inspected and those epochs retaining significant artifact (e.g., eye-blink, muscle activity, etc.) were excluded from further analyses. The remaining epochs were averaged for each of the three conditions. Finally, the average amplitudes for each of the three components of interest were derived for the following time windows: N1 (100-130 ms), P2 (190-240 ms), and P3a (270-370 ms).

Statistical Analysis

The following ANOVA designs employed a Greenhouse-Geisser correction when sphericity was violated and a Benjamini-Hochberg correction for unplanned post-hoc comparisons unless otherwise specified. Conventional degrees of freedom are reported throughout the results section.

Self-report

A series of ANOVAs with Challenge as the within-subjects factor was employed to test participants' subjective workload measured via the six items in the NASA TLX for each of the three scenarios.

Performance

A one-way ANOVA was performed using the performance metric scores across the three scenarios.

EEG - Spectral measures

A series of ANOVAs (3 (Challenge) x 3 (Period) x 4 (Electrode)) was performed to test for effects for all frequency bands of interest. The sole exception to this design was the ratio between frontal theta and parietal alpha which used a 3 (Challenge) x 3 (Period) ANOVA design.

EEG - ERP

A series of ANOVAs (3 (Challenge) x 4 (Electrode)) was performed to test for effects in the three components. Subsequent one-way ANOVAs were conducted for the factor Challenge for each component and, separately, for each electrode.

ECG - HRV

A one-way ANOVA with Challenge as the within-subject factor was performed to test for effects.

Relationship between the ERP and spectral measures

To test the relationship between measures thought to be indicative of workload and measures thought to be indicative of attentional reserve, difference scores were calculated for measures of interest between the three scenarios (S1-S2, S1-S3, and S2-S3) for each measure and Pearson correlations were performed between those difference scores. The use of difference scores was dictated by the desire to assess the relationships between the directionality of the changes across the levels of challenge among the spectral measures of cortical activation and the ERP measures. If the spectral measures exhibit an expected increase as challenge increases (revealing negative difference scores) and the ERP measures exhibit an expected decrease as challenge increases (revealing positive difference scores), the predicted negative relationship between the two measures and the concepts behind them (mental workload and attentional reserve, respectively) will be observed. The difference scores also had the added benefit of being normalized as opposed to the raw scores.

Finally, to test whether the family of spectral measures of cortical activation have a negative relationship with the family of ERP measures, collectively, a canonical correlation analysis was conducted. The canonical correlation analysis seeks several linear combinations of the ERP variables and the same number of linear combinations of spectral measure variables in such a way that these linear combinations best express the correlations between the two sets of variables. Importantly, ERP and spectral measures have been argued to be not independent of each other (Intriligator & Polich, 1994; Jansen & Brandt, 1991), making canonical correlation an appropriate analysis. Although the three ERP measures (i.e., N1, P2, and P3) and six spectral measures (i.e., theta, low alpha, high alpha, alpha, beta, and the theta/alpha ratio) were each measured at multiple electrode sites (i.e. Fz, FCz, Cz and Pz), the analysis utilized specific electrode sites for certain measures based upon established literature (i.e., N1 at Cz, P2 at Cz (Allison & Polich, 2008; Dyke et al., 2015), Theta at Fz (Cavanagh & Frank, 2014; Jensen & Tesche, 2002), Alpha (low, high, and broadband) at Pz (Jensen, Gelfand, Kounios, & Lisman, 2002; Sauseng, Klimesch, Schabus, & Doppelmayr, 2005)) and all four sites for measures in which the literature was not unified or did not indicate a specific region/site-of-interest (i.e., P3a (Dyke et al., 2015; Miller et al., 2011; Roy, Bonnet, Charbonnier, Jallon, & Campagne, 2015), Beta (Basile et al., 2007; Gola, Magnuski, Szumska, & Wróbel, 2013; Ray & Cole, 1985), and the Theta/Alpha ratio either at single electrode sites (i.e., Fz-theta/Fz-alpha) (Gentili et al., Submitted) or across frontal and parietal sites (i.e., Fz-theta/Pz-alpha) (Hockey et al., 2009; Postma et al., 2005). P-values were acquired through Roy's largest root (Roy, 1953).

Surprise element

A one-way ANOVA with Challenge as the within-subject factor was applied to the data.

Results

Self-Report

The ANOVAs revealed effects for challenge in all self-report measures (statistics shown in Table 1), such that the easy condition was rated easier than the medium condition which was rated easier than the hard condition. Planned comparisons revealed that all levels of challenge were significantly different from all others except the fifth VAS question concerning tiredness, which showed no difference between the easy and medium conditions, and the second NASA TLX question concerning physical demand, which showed only showed a difference between easy and hard conditions (see Figure 1).

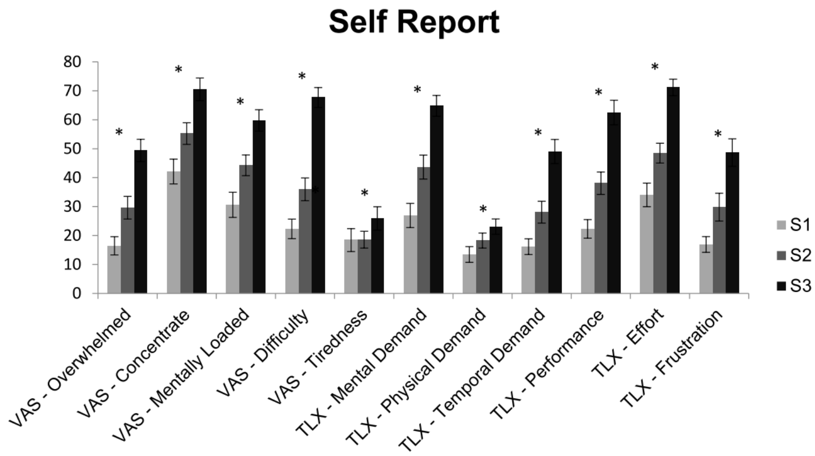

Figure 1. VAS and NASA-TLX scores across the three levels of challenge. * : $p<0.05$

Table 1. ANOVA results for self-report measures.

Measure	**F-value**	**P**	**Partial eta squared (η_p^2)**
VAS1 (Overwhelmed)	F(2,50) = 35.064	< 0.001	0.584
VAS2 (Concentration)	F(2,50) = 22.430	< 0.001	0.473
VAS3 (Mental Load)	F(2,50) = 25.115	< 0.001	0.501
VAS4 (Difficulty)	F(2,50) = 86.280	< 0.001	0.775
VAS5 (Tired)	F(2,50) = 4.007	0.024	0.138
TLX1 (Mental Demand)	F(2,50) = 49.287	< 0.001	0.663
TLX2 (Physical Demand)	F(2,50) = 5.762	0.006	0.187
TLX3 (Temporal Demand)	F(2,50) = 39.358	< 0.001	0.612
TLX4 (Failure)	F(2,50) = 34.488	< 0.001	0.580
TLX5 (Effort)	F(2,50) = 47.102	< 0.001	0.653
TLX6 (Frustration)	F(2,50) = 29.942	< 0.001	0.545

ECG-HRV

The ANOVA featuring the RMSSD measure of HRV failed to reveal any significant differences between the various challenge conditions.

Performance

The one-way ANOVA revealed a main effect for challenge ($F(2,52)=28.480$, $p<0.001$, $\eta_p^2=0.523$) such that participants performed better during the easy condition than the medium condition ($p<0.001$, $d=1.111$) and the hard condition ($p<0.001$, $d=1.661$) and better in the medium condition than the hard condition ($p<0.001$, $d=1.505$; see Figure 2).

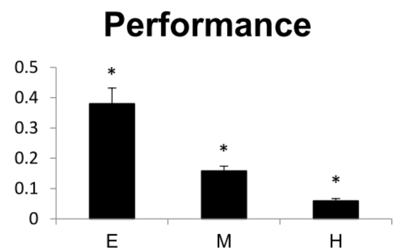

Figure 2. Performance across the three levels of challenge. * : $p<0.05$

EEG – Spectral Measures

Please see Figure 3 for a graphical representation of these results.

Theta power

Theta revealed no main effects for challenge or period. There was a main effect of electrode ($F(3,78)=20.295$, $p<0.001$, $\eta_p^2=0.438$), which was superseded by an interaction between period and electrode ($F(6,156)=3.901$, $p=.007$, $\eta_p^2=0.130$), such that theta power was strongest at frontal electrode sites at the second and third timepoints.

Broadband alpha power

Broadband alpha revealed a main effect of challenge ($F(2,52)=13.997$, $p<0.001$, $\eta_p^2=0.350$, such that easy elicited more alpha power than both medium and hard (easy vs medium: $p=0.033$, $d=0.147$; easy vs hard: $p<0.001$, $d=0.328$) and medium showed more alpha power than hard (p=0.004, d=0.185). There was also a main effect of period ($F(2,52)=18.854$, $p<0.001$, $\eta_p^2=0.420$), such that alpha power was lower in the early period of the scenario than the middle ($p<0.001$, $d=0.213$) and late ($p<0.001$, $d=0.263$) periods. Lastly there was a main effect of electrode ($F(3,78)=3.653$, $p=0.042$, $\eta_p^2=0.123$), but this was superseded by an interaction between challenge and electrode ($F(6,156)=3.209$, $p=0.016$, $\eta_p^2=0.110$), such that, while alpha power tended to be stronger at posterior electrode sites compared to frontal electrode sites, frontal sites were more sensitive to differences between the easy and medium levels of challenge, while posterior sites were more sensitive to differences between medium and hard levels of challenge.

Low-alpha power

Low alpha revealed a main effect of challenge ($F(2,52)=6.269$, $p=0.004$, $\eta_p^2=0.194$), such that easy revealed more alpha power than both medium and hard (easy vs medium: $p=0.021$, $d=0.145$; easy vs hard: $p=0.004$, $d=0.212$), which were undifferentiated. There was also a main effect of period ($F(2,52)=6.992$, $p=0.005$, $\eta_p^2=0.212$), such that low alpha increased from the first 2 min to the middle 2 min and to the last 2 min (early vs middle: $p=0.005$, $d=0.173$; early vs late: $p=0.010$, $d=0.190$). There were no other significant main effects or interactions.

High-alpha power

High alpha revealed a main effect of challenge ($F(2,52)=18.013$, $p<0.001$, $\eta_p^2=0.409$), such that high alpha power was significantly higher in both the easy and medium condition compared to the hard condition (easy vs hard: $p<0.001$, $d=0.388$; medium vs hard: $p<0.001$, $d=0.269$); easy and medium were undifferentiated. There was also a main effect of period ($F(2,52)=22.812$, $p<0.001$, $\eta_p^2=0.467$), such that high alpha increased from the first 2 min to the middle 2 min and to the last 2 min (early vs middle: $p<0.001$, $d=0.224$; early vs late: $p<0.001$, $d=0.287$); middle and late were undifferentiated. Lastly there was a main effect of electrode ($F(3,78)=14.964$, $p<0.001$, $\eta_p^2=0.365$) which was superseded by an interaction between challenge and electrode ($F(6,156)=4.235$, $p=0.003$, $\eta_p^2=0.140$), such that high alpha power was higher at posterior electrode sites compared to frontal electrode sites, but frontal electrode sites appeared to be more sensitive to differences between levels of challenge. There were no other significant main effects or interactions.

Beta power

Beta revealed an interaction between period and electrode ($F(6,156)=3.147$, $p=0.006$, $\eta_p^2=0.108$) such that beta power had a positive relationship with period at the frontal site Fz (early vs late: $p=0.023$, $d=0.118$; middle vs late: $p=0.049$, $d=0.065$). However, no pairwise comparisons remained significant after the Benjamini-Hochberg correction. There were no other significant main effects or interactions.

Theta/Alpha

The theta/alpha ratio measured within a single electrode site revealed a main effect for challenge ($F(2,52)=10.408$, $p<0.001$, $\eta_p^2=0.286$), such that both easy and medium conditions revealed a smaller theta/alpha ratio than the hard condition (easy vs hard: $p<0.001$, $d=0.377$; medium vs hard: $p=0.010$, $d=0.235$). There was also a main effect for period ($F(2,52)=13.052$, $p<0.001$, $\eta_p^2=0.334$), such that the theta/alpha ratio during the early period was larger than in both the middle and late conditions (early vs middle: $p=0.001$, $d=0.206$; early vs late: $p<0.001$, $d=0.320$). Lastly, there was a main effect for electrode ($F(3,78)=59.029$, $p<0.001$, $\eta_p^2=0.694$) which was superseded by an interaction between challenge and electrode ($F(6,156)=6.235$, $p<0.001$, $\eta_p^2=0.193$) such that theta/alpha ratio values were larger at frontal electrodes while being more sensitive to changes in level of challenge at posterior electrodes. There were no other significant interactions.

The frontal-theta/parietal-alpha ratio revealed a main effect of challenge ($F(2,52)=5.725$, $p=0.006$, $\eta_p^2=0.180$), such that the ratio was larger in both easy and medium conditions relative to the hard condition (easy vs hard: $p=0.018$, $d=0.229$; medium vs hard: $p=0.003$, $d=0.226$). There was also a main effect for period ($F(2,52)=6.062$, $p=0.004$, $\eta_p^2=0.189$) such that the ratio was smaller in the early period of the task relative to the middle and late periods (early vs middle: $p=0.018$, $d=0.133$; early vs late: $p=0.006$, $d=0.181$). There was no interaction between challenge and period.

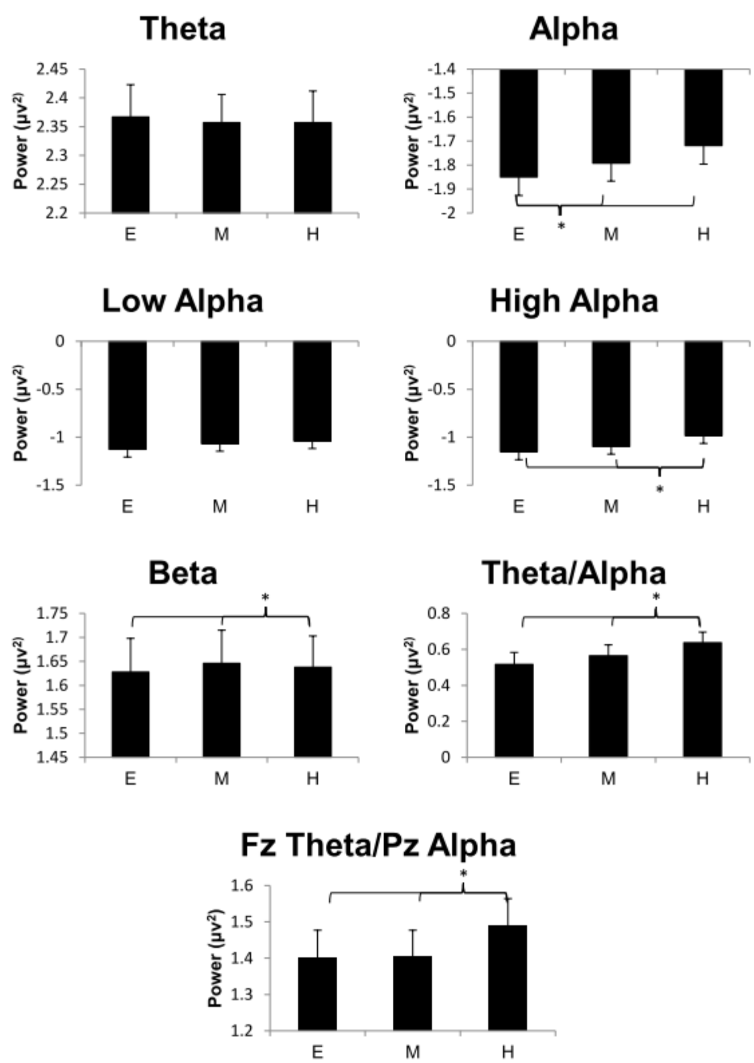

Figure 3. Spectral power across the three levels of challenge. * : $p<0.05$

EEG - ERP

Please see Figure 4 for a graphical representation of these results.

N1

The amplitude of the N1 component revealed a main effect of electrode ($F(3,78)=32.359$, $p<0.001$, $\eta_p^2=0.554$) such that N1 amplitude was maximal at the central midline site of Cz, followed closely by the fronto-central midline site of FCz

(Fz<FCz: $p<0.001$, $d=0.615$; Fz<Cz: $p<0.001$, $d=0.705$; FCz>Pz: $p<0.001$, $d=0.836$; Cz>Pz: $p<0.001$, $d=0.911$). There were no other main effects or interactions. Further planned ANOVAs using individual electrodes failed to reveal any further effects with no clear trends emerging.

P2

The amplitude of the P2 component revealed a main effect of electrode ($F(3, 78)=21.098$, $p<0.001$, $\eta_p^2=0.448$) such that P2 amplitude was maximal at the central midline site of Cz, followed closely by the fronto-central midline site of FCz (Fz<FCz: $p<0.001$, $d=0.742$; Fz<Cz: $p<0.001$, $d=0.962$; FCz<Cz: $p=0.008$, $d=0.265$; FCz>Pz: $p<0.001$, $d=0.888$; Cz>Pz: $p<0.001$, $d=1.101$). There were no other main effects or interactions. Further planned ANOVAs using individual electrodes failed to reveal any further effects despite trends for the P2 amplitude to reduce as level of challenge increased.

P3a

There were no main effects or interactions found for the amplitude of the P3a component. However, planned comparisons of P3a amplitudes at electrode Cz revealed a significant effect of challenge $F(2,52)=3.782$, $p=0.029$, $\eta_p^2=0.127$), such that the easy condition revealed larger P3a amplitudes than the medium or hard conditions (easy vs medium: $p=0.036$, $d=0.507$; easy vs hard: $p=0.031$, $d=0.399$); medium and hard were undifferentiated.

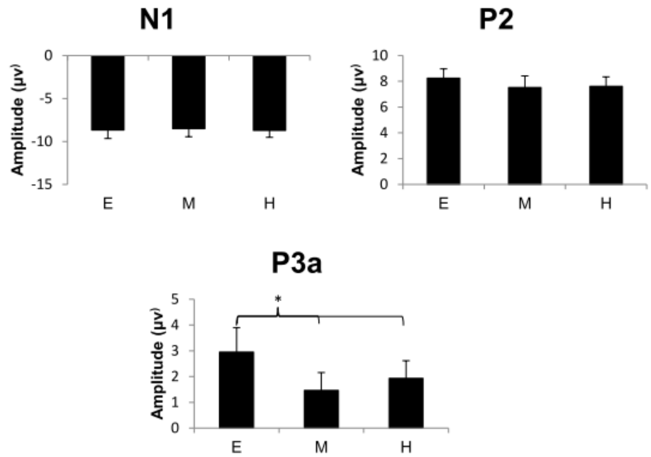

Figure 4. ERP amplitudes across the three levels of challenge. * : p<0.05 at Cz only.

Correlations

Bivariate correlations revealed mostly negative relationships between spectral measures of cortical activation and the ERP measures (see Table 2), save for the relationship between P3 amplitude at FCz and Theta band power at FCz which was positive.

Table 2. Significant bivariate correlations. P-values are uncorrected.

Difference score	**ERP - Site**	**Frequency - Site**	**r**	**P**
Easy - Medium	P2 - FCz	Low Alpha - Pz	-0.467	0.014
Easy - Hard	N1 - Pz	Alpha - Pz	-0.404	0.037
		High Alpha - Pz	-0.403	0.037
	P2 - FCz	Alpha - Pz	-0.417	0.031
		Low Alpha - Pz	-0.606	0.001
		Theta/Alpha - Fz	-0.415	0.031
		Theta/Alpha - Cz	-0.421	0.029
	P2 - Cz	Theta/Alpha - Fz	-0.463	0.015
		Theta/Alpha - FCz	-0.428	0.026
		Theta/Alpha - Cz	-0.484	0.010
	P3 - FCz	Theta - FCz	0.464	0.015

Using all spectral measures of cortical activation (Theta (Fz); Alpha (Pz); Beta (Fz, FCz, Cz, & Pz); & Theta/Alpha (Fz, FCz, Cz, Pz, & Fz-Theta/Pz-Alpha)) and all ERP measures (N1 (Cz), P2 (Cz), P3a (Fz, FCz, Cz, & Pz)), the canonical correlations between the ERP and spectral measures of cortical activation are as follows: S1-S2 = -0.955, $p<0.001$; S1-S3 = -0.929, $p=0.001$; and S2-S3 = -0.933, $p=0.001$. There appears to be a strong negative association between the spectral measures of cortical activation and the ERP measures (see Figure 5).

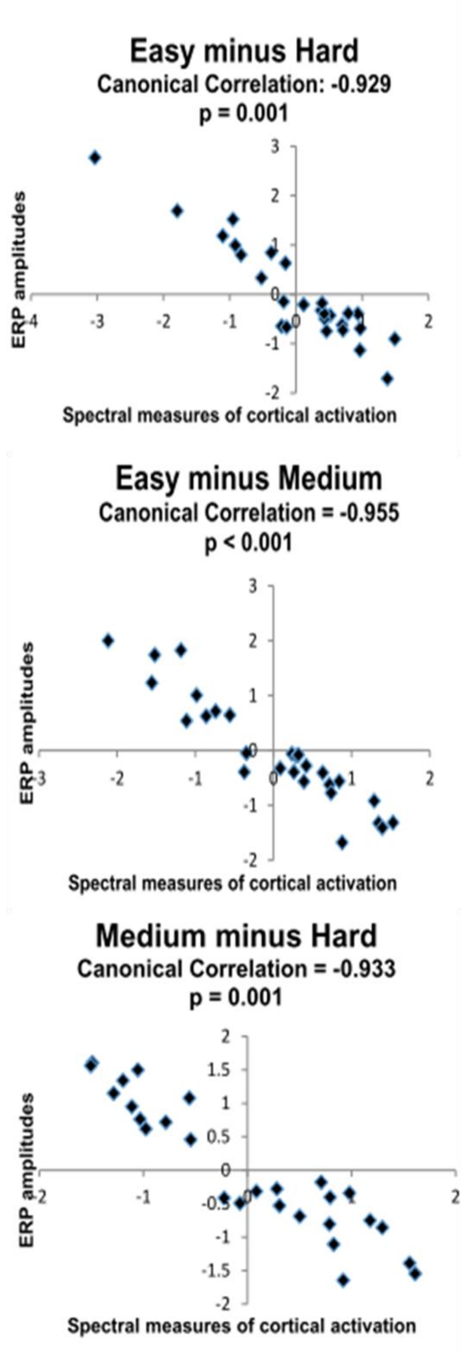

Figure 5. Scatterplots of individual scores of the canonical correlation for spectral measures of cortical activation (theta, low alpha, high alpha, alpha, beta, and the theta/alpha ratio) and ERP amplitudes (N1, P2, and P3a). As canonical correlation always mathematically yields a positive relationship, coefficient values for the

spectral measures of cortical activation were multiplied by (-1) to illustrate the theoretically interpreted inverse relationship between mental workload and attentional reserve.

Surprise Element

The ANOVA featuring the surprise element, the recognition of the Master Warning light on the instrument panel, failed to reveal any differences among the various levels of challenge.

Discussion

The goal of this study was to empirically demonstrate the existence of an inverse relationship between measures believed to represent two opposing elements of cognition: mental workload and attentional reserve. Measures of mental workload included spectral measures of cortical activation (i.e., theta, alpha, beta, and the theta/alpha ratio) while measures of attentional reserve included ERP amplitudes from "novel" auditory probes (Fabiani et al., 1996; Miller et al., 2011). Broadly, this goal was met; results from the canonical correlation analysis revealed a strong negative relationship between the measures of workload and the measures of reserve. These results offer support for the speculation that the spectral measures of cortical activation and the ERP amplitudes are representative of the concepts of mental workload and attentional reserve, respectively.

The self-report results provided confidence of a successful manipulation as all elements of the NASA-TLX and VAS increased as level of challenge increased. Measures of heart rate variability, however, did not reduce with increased task demand as expected. It has been indicated that HRV measures may be related to top-down appraisals of the environment and can be viewed as an index of adaptive regulation of the bodily systems (i.e., cognition, perception, action, physiology) such that HRV is positively related to this adaptive behavior (Thayer, Åhs, Fredrikson, Sollers, & Wager, 2012; Thayer, Hansen, Saus-Rose, & Johnsen, 2009). The present finding of no difference between levels of challenge may indicate that three levels of challenge did not affect the homeostatic state of the bodily system or the appraisal of the environment despite varying levels of subjective experience, such as differential feelings of effort and frustration. This is encouraging as the flight scenarios employed in this experiment were not intended to manipulate the homeostatic properties of the body; instead they were intended to instigate differential loads on the cognitive system. Lastly, the surprise element, which served as a behavioral correlate of workload, was not sensitive to changes in the level of challenge. This may be due to the positioning of the surprise element in the gauge cluster of the aircraft. Since the gauges were integral to the successful performance of the task, especially during the medium and hard scenarios, visual attention was very often focused on the gauge cluster and within the area the surprise element appeared. Perhaps by placing the surprise element in a less attended to location would yield more expected results.

Among the measures of mental workload, alpha, and the theta/alpha ratio behaved as expected, revealing increases in cortical activation and mental workload. Theta, however, failed to reveal any effects of interest. Theta has been indeed been linked to mental workload (Gevins & Smith, 2003; Hankins & Wilson, 1998; Rietschel et al., 2012), but is more broadly associated with working memory function including integration and encoding (Klimesch, 1999; Sauseng, Griesmayr, Freunberger, & Klimesch, 2010). Given that the presently utilized experimental task is highly complex and the fact that the participants were novices, it is reasonable to think that the demand on working memory would be relatively constant across levels of challenge. This is supported by the fact that previous experiments finding a relationship between theta and workload used simple laboratory tasks (Gevins & Smith, 1999; Rietschel et al., 2012) or skilled participants (Hankins & Wilson, 1998). Given the high complexity levels of the flight simulator task, perhaps allowing participants to practice and learn the task over time would allow for better task discrimination with theta power as working memory engagement during a task is thought to reduce with learning (Fitts & Posner, 1967). Similarly, beta failed to reveal any effects of interest. Though beta has been linked with task demand, it has also been associated with a plethora of other constructs that this experiment may or may not have controlled for such as emotional processing (Ray & Cole, 1985), stress (Mauri et al., 2010), movement planning and execution (Klostermann et al., 2007), and attentional processing (Gola et al., 2013). Future work should better control for these myriad elements in order to further investigate beta's relationship with mental workload.

Among the ERP amplitude measures of attentional reserve, the P3a revealed an expected effect of challenge, reducing as challenge increases at site Cz. This result supports previous findings showing that the P3a or "novelty P3" decreases in amplitude as mental workload increases (Miller et al., 2011; Rietschel et al., 2014). Other components also showed expected directional trends, albeit not significant, similar to Rietschel et al. (2014). The auditory N1 has been indicated of being representative of sensory and early attentional processing (Hansen & Hillyard, 1980) while the P2 has been indicated of being representative of attention allocation (Miller et al., 2011; Picton & Hillyard, 1974) and the orienting response (Kanske, Plitschka, & Kotz, 2011) and has been shown to be sensitive to task engagement (Leiker et al., 2016). It is possible that the most challenging scenario elicited a reduction in task engagement because the degree of challenge may have been excessive. This view is supported in part by the P3a results showing a slight increase from the medium scenario to the hard scenario, perhaps indicating a small increase in attentional reserve. These results may serve to highlight the specificity of the P3a as an indicator of attentional reserve. That said, although the effects of the ERP components are necessary to understand how the ERP represents attentional reserve, it is not sufficient to assess the components in isolation and can have utility when analyzed collectively (Roy, Bonnet, Charbonnier, & Campagne, 2012).

Although the individual measures have their merits, alone they have limited impact on the measurement of our constructs of interest, mental workload and attentional reserve. The results of the canonical correlation, which analyzed these variables as members of two distinct "families" of measures, revealed a strong negative relationship between the spectral measures of cortical activation and the ERP measures. To our knowledge, this is the first instance of empirical evidence showing such a relationship between these two theoretically opposed constructs. These findings support previous and intuitive notions (Broadbent, 1957; Kahneman, 1973; Kantowitz, 1987; Wickens, 2002) that capacity is indeed limited and, on the most basic level, consists of two aspects: that which is being used (i.e., mental workload) and that which is in reserve (i.e., attentional reserve).

Of course, the approach used in this experiment has limitations. A relatively low sensor count was used for EEG recording with a mind toward practical application. This did, however, place a limit on the analyses that could be performed with the data. A more comprehensive sensor array will benefit future studies of mental workload and attentional reserve, specifically if source localization is critical to the research question. Additionally, while ERPs are very useful to investigate the temporal structure of specific cognitive phenomena, they are not well-suited to real-world, real-time application due to the need to average a number of trials to attain a reliable waveform. Work in the realm of single trial ERPs (Delorme & Makeig, 2004; Jung et al., 2001) may lead to change in this regard, but it is worth pointing out this limitation if the focus of attentional reserve measurement is practical application. The last, and perhaps most critical, limitation is a lack of reference or anchor points when investigating and discussing mental workload and attentional reserve. While it can be said with some level of confidence based upon the present results that as mental workload increases, attentional reserve decreases, science is presently unaware of suitable methodology to assess the upper and lower bounds of human cognitive capacity, nor is it understood how this capacity is impacted by task demand. Without this knowledge, it is unclear the extent of cognitive capacity that is explained by presently utilized metrics. Future research should work to expand the knowledge base in this regard. It would also be beneficial to observe how these correlates of mental workload change over time, specifically during the learning process. While the present study, among others (Ryu & Myung, 2005; Sassaroli et al., 2008; Shuggi, Oh, Shewokis, & Gentili, 2017; Wilson, 2002), assessed task-related changes in mental workload during a single performance session, the temporal dynamics of mental workload and its constituents related to learning remains unclear.

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References

Allison, B. Z., & Polich, J. (2008). Workload assessment of computer gaming using a single-stimulus event-related potential paradigm. Biological Psychology, 77(3), 277-283.

Basile, L. F., Anghinah, R., Ribeiro, P., Ramos, R. T., Piedade, R., Ballester, G., & Brunetti, E. P. (2007). Interindividual variability in EEG correlates of attention and limits of functional mapping. International Journal of Psychophysiology, 65(3), 238-251.

Broadbent, D. E. (1957). A mechanical model for human attention and immediate memory. Psychological Review, 64(3), 205.

Brouwer, A.-M., Hogervorst, M. A., Van Erp, J. B., Heffelaar, T., Zimmerman, P. H., & Oostenveld, R. (2012). Estimating workload using EEG spectral power and ERPs in the n-back task. Journal of Neural Engineering, 9(4), 045008.

Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. Trends in Cognitive Sciences, 18(8), 414-421.

Chang, G. H. L. Y. H., & Lin, K. P. (2005). Comparison of heart rate variability measured by ECG in different signal lengths. Journal of Medical and Biological Engineering, 25(2), 67-71.

Cinaz, B., Arnrich, B., La Marca, R., & Tröster, G. (2013). Monitoring of mental workload levels during an everyday life office-work scenario. Personal and Ubiquitous Computing, 17(2), 229-239.

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of Neuroscience Methods, 134(1), 9-21.

Dyke, F. B., Leiker, A. M., Grand, K. F., Godwin, M. M., Thompson, A. G., Rietschel, J. C., . . . Miller, M. W. (2015). The efficacy of auditory probes in indexing cognitive workload is dependent on stimulus complexity. International Journal of Psychophysiology, 95(1), 56-62.

Fabiani, M., Kazmerski, V. A., Cycowicz, Y. M., & Friedman, D. (1996). Naming norms for brief environmental sounds: Effects of age and dementia. Psychophysiology, 33(4), 462-475.

Gentili, R. J., Jaquess, K. J., Shuggi, I. M., Oh, H., Lo, L.-C., Tan, Y. Y., . . . Hatfield, B. D. (Submitted). Assessment of a dry EEG system for multimodal assessment of cognitive workload under various level of challenge: Towards ecological applications in the field.

Gevins, A., & Smith, M. E. (1999). Detecting transient cognitive impairment with EEG pattern recognition methods. Aviation, Space, and Environmental Medicine, 70(10), 1018-1024.

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. Theoretical Issues in Ergonomics Science, 4(1-2), 113-131.

Gola, M., Magnuski, M., Szumska, I., & Wróbel, A. (2013). EEG beta band activity is related to attention and attentional deficits in the visual performance of elderly subjects. International Journal of Psychophysiology, 89(3), 334-341.

Hankins, T. C., & Wilson, G. F. (1998). A comparison of heart rate, eye activity, EEG and subjective measures of pilot mental workload during flight.

Aviation, Space, and Environmental Medicine, 69(4), 360-367.

Hansen, J. C., & Hillyard, S. A. (1980). Endogeneous brain potentials associated with selective auditory attention. Electroencephalography and Clinical Neurophysiology, 49(3), 277-290.

Hart, S. G. (2006). NASA-task load index (NASA-TLX); 20 years later. Paper presented at the proceedings of the Human Factors and Ergonomics Society annual meeting.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in Psychology, 52, 139-183.

Hockey, G. R. J., Nickel, P., Roberts, A. C., & Roberts, M. H. (2009). Sensitivity of candidate markers of psychophysiological strain to cyclical changes in manual control load during simulated process control. Applied Ergonomics, 40(6), 1011-1018.

Intriligator, J., & Polich, J. (1994). On the relationship between background EEG and the P300 event-related potential. Biological Psychology, 37(3), 207-218.

Jansen, B. H., & Brandt, M. E. (1991). The effect of the phase of prestimulus alpha activity on the averaged visual evoked response. Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section, 80(4), 241-250.

Jensen, O., Gelfand, J., Kounios, J., & Lisman, J. E. (2002). Oscillations in the alpha band (9–12 Hz) increase with memory load during retention in a short-term memory task. Cerebral Cortex, 12(8), 877-882.

Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. European Journal of Neuroscience, 15(8), 1395-1399.

Jung, T. P., Makeig, S., Westerfield, M., Townsend, J., Courchesne, E., & Sejnowski, T. J. (2001). Analysis and visualization of single-trial event-related potentials. Human Brain Mapping, 14(3), 166-185.

Kahneman, D. (1973). Attention and effort: Citeseer.

Kanske, P., Plitschka, J., & Kotz, S. A. (2011). Attentional orienting towards emotion: P2 and N400 ERP effects. Neuropsychologia, 49(11), 3121-3129. doi: http://dx.doi.org/10.1016/j.neuropsychologia.2011.07.022

Kantowitz, B. H. (1987). 3. Mental Workload. Advances in psychology, 47, 81-121.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Research Reviews, 29(2–3), 169-195. doi: http://dx.doi.org/10.1016/S0165-0173(98)00056-3

Klostermann, F., Nikulin, V. V., Kühn, A. A., Marzinzik, F., Wahl, M., Pogosyan, A., . . . Curio, G. (2007). Task-related differential dynamics of EEG alpha-and beta-band synchronization in cortico-basal motor structures. European Journal of Neuroscience, 25(5), 1604-1615.

Leiker, A. M., Miller, M., Brewer, L., Nelson, M., Siow, M., & Lohse, K. (2016). The Relationship Between Engagement and Neurophysiological Measures of Attention in Motion-Controlled Video Games: A Randomized Controlled Trial. JMIR Serious Games, 4(1).

Mauri, M., Magagnin, V., Cipresso, P., Mainardi, L., Brown, E. N., Cerutti, S., . . . Barbieri, R. (2010, Aug. 31 2010-Sept. 4 2010). Psychophysiological signals associated with affective states. Paper presented at the 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology.

Mehler, B., Reimer, B., & Wang, Y. (2011). A comparison of heart rate and heart rate variability indices in distinguishing single task driving and driving under secondary cognitive workload. Paper presented at the Proc Driving Symposium on Human Factors in Driver Assessment.

Miller, M. W., Rietschel, J. C., McDonald, C. G., & Hatfield, B. D. (2011). A novel approach to the physiological measurement of mental workload. International Journal of Psychophysiology, 80(1), 75-78. doi: http://dx.doi.org/10.1016/j.ijpsycho.2011.02.003

Munoz, M. L., van Roon, A., Riese, H., Thio, C., Oostenbroek, E., Westrik, I., . . . Nolte, I. M. (2015). Validity of (Ultra-) Short Recordings for Heart Rate Variability Measurements. PloS one, 10(9), e0138921.

Nassef, A., Mahfouf, M., Linkens, D., Elsamahy, E., Roberts, A., Nickel, P., . . . Panoutsos, G. (2009). The assessment of Heart Rate Variability (HRV) and Task Load Index (TLI) as physiological markers for physical stress. Paper presented at the World Congress on Medical Physics and Biomedical Engineering, September 7-12, 2009, Munich, Germany.

Picton, T., & Hillyard, S. (1974). Human auditory evoked potentials. II: Effects of attention. Electroencephalography and Clinical Neurophysiology, 36, 191-200.

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. Clinical Neurophysiology, 118(10), 2128-2148.

Postma, M. A., Schellekens, J., Hanson, E. K., & Hoogeboom, P. J. (2005). Fz theta divided by Pz alpha as an index of task load during a PC-based air traffic control simulation (pp. 1-5): Shaker Publishing, Maastricht, The Netherlands.

Ray, W. J., & Cole, H. W. (1985). EEG alpha activity reflects attentional demands, and beta activity reflects emotional and cognitive processes. Science, 228, 750-752.

Rietschel, J. C., McDonald, C. G., Goodman, R. N., Miller, M. W., Jones-Lush, L. M., Wittenberg, G. F., & Hatfield, B. D. (2014). Psychophysiological support of increasing attentional reserve during the development of a motor skill. Biological Psychology, 103, 349-356.

Rietschel, J. C., Miller, M. W., Gentili, R. J., Goodman, R. N., McDonald, C. G., & Hatfield, B. D. (2012). Cerebral-cortical networking and activation increase as a function of cognitive-motor task difficulty. Biological Psychology, 90(2), 127-133. doi: http://dx.doi.org/10.1016/j.biopsycho.2012.02.022

Roy, R., Bonnet, S., Charbonnier, S., & Campagne, A. (2012). Time-on-task effect on workload level discriminability through electroencephalography. Paper presented at the 18th International Conference on Biomagnetism (BIOMAG 2012).

Roy, R. N., Bonnet, S., Charbonnier, S., Jallon, P., & Campagne, A. (2015). A comparison of ERP spatial filtering methods for optimal mental workload estimation. Paper presented at the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).

Roy, S. N. (1953). On a heuristic method of test construction and its use in multivariate analysis. The Annals of Mathematical Statistics, 220-238.

Ryu, K., & Myung, R. (2005). Evaluation of mental workload with a combined measure based on physiological indices during a dual task of tracking and mental arithmetic. International Journal of Industrial Ergonomics, 35(11), 991-1009.

Sanders, A. (1979). Some remarks on mental load Mental workload (pp. 41-77): Springer.

Sassaroli, A., Zheng, F., Hirshfield, L. M., Girouard, A., Solovey, E. T., Jacob, R. J., & Fantini, S. (2008). Discrimination of mental workload levels in human subjects with functional near-infrared spectroscopy. Journal of Innovative Optical Health Sciences, 1(02), 227-237.

Sauseng, P., Griesmayr, B., Freunberger, R., & Klimesch, W. (2010). Control mechanisms in working memory: a possible function of EEG theta oscillations. Neuroscience & Biobehavioral Reviews, 34(7), 1015-1022.

Sauseng, P., Klimesch, W., Schabus, M., & Doppelmayr, M. (2005). Fronto-parietal EEG coherence in theta and upper alpha reflect central executive functions of working memory. International Journal of Psychophysiology, 57(2), 97-103.

Shuggi, I. M., Oh, H., Shewokis, P. A., & Gentili, R. J. (2017). Mental workload and motor performance dynamics during practice of reaching movements under various levels of task difficulty. Neuroscience, 360, 166-179.

Thayer, J. F., Åhs, F., Fredrikson, M., Sollers, J. J., & Wager, T. D. (2012). A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. Neuroscience &

Biobehavioral Reviews, 36(2), 747-756.

Thayer, J. F., Hansen, A. L., Saus-Rose, E., & Johnsen, B. H. (2009). Heart rate variability, prefrontal neural function, and cognitive performance: the neurovisceral integration perspective on self-regulation, adaptation, and health. Annals of Behavioral Medicine, 37(2), 141-153.

Thong, T., Li, K., McNames, J., Aboy, M., & Goldstein, B. (2003). Accuracy of ultra-short heart rate variability measures. Paper presented at the Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE.

Wickens, C. D. (2002). Multiple resources and performance prediction. Theoretical Issues in Ergonomics Science, 3(2), 159-177.

Wilson, G. F. (2002). An analysis of mental workload in pilots during flight using multiple psychophysiological measures. The International Journal of Aviation Psychology, 12(1), 3-18.

Chapter 3: Transition from Study 1 to Study 2

The results of study 1 provided evidence that cognitive resources can be index via measures of cortical dynamics. Specifically, EEG spectral measures of cortical activation were shown to be indicative of mental workload while component amplitudes from ERPs generated by unattended novel sounds were shown to be indicative of attentional reserve. This study provides confidence that cognitive processes related to mental workload can be measured via EEG. Two questions one may ask with this knowledge is how does mental workload changes with 1) task difficulty and 2) over the course of practice. While studies have been conducted investigating the effects of task difficulty and practice on mental workload in isolation (Gentili et al., 2018; Jaquess et al., 2017; Kerick, Douglass, & Hatfield, 2004; Rietschel et al., 2014), no study had investigated the potential interactive effects of task difficulty and practice on mental workload. The next study provides some evidence to address this empirical question.

References

Gentili, R. J., Jaquess, K. J., Shuggi, I. M., Shaw, E. P., Oh, H., Lo, L. C., . . . Hatfield, B. D. (2018). Combined assessment of attentional reserve and cognitive-motor effort under various levels of challenge with a dry EEG system. Psychophysiology.

Jaquess, K. J., Gentili, R. J., Lo, L. C., Oh, H., Zhang, J., Rietschel, J. C., . . . Hatfield, B. D. (2017). Empirical evidence for the relationship between cognitive workload and attentional reserve. International Journal of Psychophysiology, 121, 46-55. doi: https://doi.org/10.1016/j.ijpsycho.2017.09.007

Kerick, S. E., Douglass, L. W., & Hatfield, B. D. (2004). Cerebral cortical adaptations associated with visuomotor practice. Medicine & Science in Sports & Exercise, 36(1), 118-129.

Rietschel, J. C., McDonald, C. G., Goodman, R. N., Miller, M. W., Jones-Lush, L. M., Wittenberg, G. F., & Hatfield, B. D. (2014). Psychophysiological support of increasing attentional reserve during the development of a motor skill. Biological Psychology, 103, 349-356.

Chapter 4: Changes in mental workload and motor performance throughout multiple practice sessions under various levels of task difficulty

Abstract

The allocation of mental workload is critical to maintain cognitive-motor performance under various task difficulties. While mental workload has been investigated during performance, a limited effort has examined it during cognitive-motor learning, while no studies concurrently manipulated task difficulty. It is reasonable to surmise that the level of difficulty at which a skill is practiced would impact the rate of skill acquisition, but also the rate at which mental workload is reduced due to learning (i.e., relatively slowed for harder compared to easier tasks). This study aims to monitor mental workload through assessment of cortical dynamics using electroencephalography (EEG) during a task practiced under two difficulty levels over four days while perceived task demand, performance, and EEG signals were collected. As expected, self-reported mental workload was reduced, greater working memory engagement via EEG theta synchrony was observed and reduced cortical activation, as indexed by EEG alpha synchrony, occurred over practice. Task difficulty was positively related to the magnitude of alpha desynchrony accompanied by elevations in the theta-alpha ratio. Counter to expectations, the absence of a between practice and difficulty interaction for both theta and alpha power indicates that the refinement of mental processes throughout learning occurred at a comparable rate for both task difficulties. Thus, the assessment of brain dynamics was sensitive to

the rate of change of cognitive workload with practice, but not to the degree of difficulty. Further work should consider a broader range of task difficulties and additional measures of brain processes to further assess this phenomenon.

Introduction

Through practice and experience, the human cognitive-motor control system can either adapt existing motor patterns to account for changing task demands or learn novel skills that result in expanding one's motor repertoire (Boutin et al., 2012; Boutin, Panzer, & Blandin, 2013; Krakauer & Mazzoni, 2011; Shadmehr & Wise, 2005). Such adaptive and learning processes rely on the engagement of appropriate mental resources during practice and performance (Boutin, Blandin, Massen, Heuer, & Badets, 2014; Gentili, Shewokis, Ayaz, & Contreras-Vidal, 2013; Rietschel et al., 2014; Seidler, Bo, & Anguera, 2012). While the recruitment of these resources tends to become more refined as a result of practice and learning, resulting in greater neural efficiency over the practice period (Ayaz et al., 2012; Cheng, Huang, et al., 2015; Gevins, Smith, McEvoy, & Yu, 1997; Shuggi, Oh, Shewokis, & Gentili, 2017; Shuggi, Shewokis, Herrmann, & Gentili, 2017), it is also the case that aspects of the task, itself, such as the performance of difficult tasks, can influence resource allocation (Ayaz et al., 2010; Gentili et al., In press; Gevins & Smith, 2003). Such changes in mental resource recruitment can be detected by employing measurements of mental workload via self-report (Hart & Staveland, 1988) and cerebral cortical dynamics (Jaquess et al., 2017; Palinko, Kun, Shyrokov, & Heeman, 2010; Shewokis et al., 2015; Shewokis et al., 2017). One could expect that the rate of diminution or attenuation of mental workload due to practice and learning, and the emergence of neural efficiency, would be proportional to task demands (i.e., relatively slowed for more challenging tasks compared to an easy tasks). While much work has been done on the assessment of mental workload, it is unclear how mental workload and cortical dynamics are influenced by task difficulty over multiple practice sessions.

The concept of mental workload implies that humans have limited information processing capabilities. Indeed, in the presence of large amounts of information, our cognitive systems can become overwhelmed, leading to declines in task learning and performance (Marteniuk, 1976; Sweller, 2010). Guadagnoli and Lee (2004) have noted that modifying task difficulty is an effective method of manipulating the informational demands placed on an individual as difficult tasks obviously contain more information than easy tasks and elevation in informational demands are positively related to mental workload (Kantowitz, 1987; Svensson, Angelborg-Thanderez, Sjöberg, & Olsson, 1997; Sweller, 2010). Learning reduces task-related workload, but the effectiveness of learning is influenced by initial information processing demands, such that learning is hindered under conditions of excessive mental workload (Marteniuk, 1976; Sweller, 2010).

Few studies have manipulated task difficulty during practice while monitoring mental workload. In one instance, by manipulating the practice difficulty of a postural control task, Akizuki and Ohashi (2015) examined changes in both mental workload and postural stability, finding that practice under moderate levels of mental workload produced better learning outcomes than practice under conditions of relatively low or high workload. Shuggi, Oh, et al. (2017), using a human-machine interface, also examined mental workload and performance dynamics during the practice of a reaching task under various levels of task difficulty, and observed that performance improved at a slower rate under high levels of mental workload as measured by the mental demand sub-scale of the NASA Task Load Index (TLX). While these studies are informative, they did not assess brain dynamics to understand how neuro-cognitive correlates of mental workload are impacted during learning under various levels of task difficulty.

To our knowledge, only one study has assessed brain dynamics utilizing electroencephalography (EEG) as a measure of cortical activation to assess changes in mental workload due to practice and variations in task difficulty (Gevins et al., 1997). Gevins et al. reported that both EEG low-alpha power (8-10Hz), which is inversely related with general arousal, and high-alpha power (10-13Hz), which is inversely related with task-related attentional processes (Budzynski, Budzynski, Evans, & Abarbanel, 2009; Haufler, Spalding, Santa Maria, & Hatfield, 2000; Smith, McEvoy, & Gevins, 1999), decreased with task difficulty and increased during only one single practice session, which is consistent with the notion that the recruitment of cortical resources increases with task demands and decreases with practice (Gentili, Bradberry, Oh, Hatfield, & Contreras Vidal, 2011; Jaiswal, Ray, & Slobounov, 2010; Kerick, Douglass, & Hatfield, 2004). It was also observed that EEG frontal theta power, which is positively related with working memory engagement and attentional control (Brookings, Wilson, & Swain, 1996; Gentili et al., In press; Shaw et al., In press) increased with both task difficulty and practice. Of note, Gevins et al. (1997) observed an interaction between task difficulty and practice time such that frontal theta power increased more across the practice session within the more difficult task than in the less difficult task, despite no such interaction being observed in terms of performance improvement.

However, it remains to be seen how these EEG correlates of mental workload behave across multiple practice sessions under varying levels of difficulty and how they translate into learning outcomes. Indeed, while observed changes within a single practice session are informative, it is unclear whether they extend to longer-term changes in cortical dynamics and performance (i.e., learning resulting from motor memory consolidation due to repeated practice) (Boutin et al., 2017; Kantak & Winstein, 2012; Krakauer & Mazzoni, 2011; Magill & Anderson, 2016; Shadmehr & Wise, 2005). Furthermore, given that previous theoretical work and behavioral studies have concluded that individuals learn best under specific levels of difficulty (Akizuki & Ohashi, 2015; Guadagnoli & Lee, 2004; Shuggi, Oh, et al., 2017), it is reasonable to expect that concomitant brain changes would also occur (Herholz & Zatorre, 2012; Kerick et al., 2004; Landers, Han, Salazar, & Petruzzello, 1994).

The present study contributes to the motor learning literature by investigating the brain dynamics related to mental workload via EEG during the practice of a novel and complex cognitive-motor task under two levels of difficulty across multiple practice sessions. Broadly, an interactive relationship was hypothesized between practice and task difficulty, such that participants would learn the task more quickly in the easy condition relative to the hard condition, while self-reported measures of task demand and EEG measures of mental workload would reflect a corresponding magnitude of change. More specifically, we predicted that ratings of mental demand and difficulty would reduce more quickly in the easy condition relative to the hard condition and that EEG theta and alpha power, more specifically high-alpha power, would increase more rapidly across practice visits in the easy relative to the hard condition. Finally, some work has indicated that a ratio of EEG theta power over EEG alpha power is an effective indicator of mental workload such that the ratio has a positive relationship with task engagement (Hockey, Nickel, Roberts, & Roberts, 2009; Nassef et al., 2009; Postma, Schellekens, Hanson, & Hoogeboom, 2005). However, no work has utilized this metric in a setting that promotes learning. Thus, we also investigated the dynamics of the theta/alpha ratio in an exploratory manner.

Methods

Participants

Thirty-six healthy right-handed participants (11 females and 15 males; mean age: 28.47 ± 7.24 yrs) took part in this study. All participants were students from the University of Maryland- College Park who gave their consent before participating in this experiment, which was approved by the university's institutional review board.

Procedure

The study protocol consisted of five visits to the lab. Upon arrival to the first session, participants were provided with a brief explanation of the experiment. After giving their informed consent, participants were escorted to a sound-attenuated chamber. Measurements of head circumference and inion-nasion distance were gathered to inform the correct EEG cap size and placement for capture of the EEG during subsequent visits (i.e., from the second to the fifth visit).

The first visit was conducted to familiarize the participants with the task, which was to control an airplane (Beechcraft T-6 Texan II) in a high-fidelity flight simulated environment (Prepar3D®, Lockheed Martin Corporation). Specifically, participants were informed of the nature of the task and the expectations regarding the desired performance outcome. Participants were provided a detailed explanation of all aircraft controls (joystick, throttle, and rudder pedals) and gauges (ex: airspeed, vertical, speed, altimeter, etc.) needed to perform successfully. Immediately after, an opportunity was provided for any questions and additional clarification, if needed.

Once the introduction to the task and testing environment was completed, the two flight scenarios, corresponding to a low (Scenario 1) and a high (Scenario 2) level of difficulty were described in detail as follows. First, the participants were told that they would perform under two conditions in which they would be flying while trying to adjust altitude and while maintaining a constant speed and direction (Figure 6A).

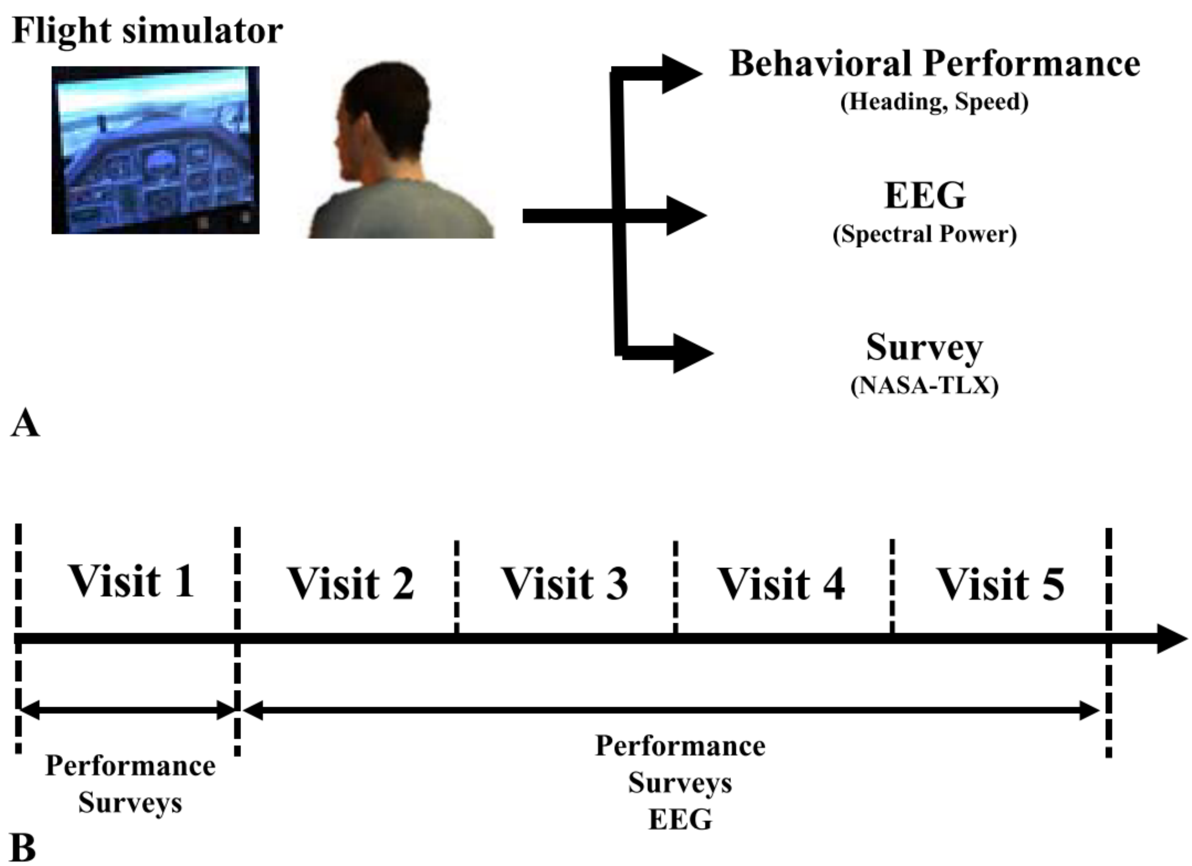

Figure 6. Experimental set-up. A. Participants practiced a flight task during five visits (from 1 to 5) under two levels of task difficulty (easy and hard). B. This first visit consisted mainly a familiarization stage with the simulators and the flight task and thus was not included in the analysis. During the first visit only the performance (plane speed and heading) and the perception of mental workload and task demand (via the NASA TLX surveys; Appendix B.) were collected. Then, during the visits 2, 3, 4 and 5, in addition to the performance and perceived mental workload, the EEG signals via a 32 active electrodes cap were also collected.

In Scenario 1 (low task difficulty), participants were told that the plane will be flying 3000 ft above the Pacific Ocean, flying due South (180 degrees) and at a speed of 180 knots. Participants were instructed to take control of the plane and to perform the following maneuvers in 1-min increments (i.e., 1 min for each maneuver). The first maneuver was to maintain 3000 ft of altitude at 180 degrees (South) and 180 knots. Second, participants were instructed to climb 1000 ft in altitude to 4000 ft at a rate of 1000 ft/min while maintaining a heading of 180 degrees and an airspeed of 180 knots. Regardless of their success at completing this maneuver within the allotted timeframe, they were asked to follow the instructions for the next objective. This was done to verify that all participants were focused on the same objective at any given time during the task. The third maneuver was to maintain an altitude of 4000 ft (or present altitude) at 180 degrees and 180 knots for 1 min. Fourth, they were instructed to descend 1000 ft in altitude back to 3000 ft and maintain 180 degrees in heading and 180 knots at a rate of 1000 ft/min. Again, regardless of their success at completing this maneuver within the allotted timeframe, they were instructed to follow the next set of instructions for the next objective. Finally, participants were asked to maintain an altitude of 3000 ft (or present altitude) at 180 degrees and 180 knots for 1 min.

In Scenario 2 (high task difficulty), the objectives and instructions were identical to the low task-difficulty scenario, but now the task was to be performed under conditions of severe turbulence, which elevated the challenge for participants to control the aircraft and keep it on course throughout the various maneuvers. Once instructions were provided to the participants, they were again provided the opportunity to ask questions and obtain clarification regarding the task, if needed.

Both scenarios lasted five min (five maneuvers each lasting 1 min), allowing only enough time for a participant to complete all of the required tasks as specified. During the task performance period, participants were informed of the passage of time and the task to be performed in one-min increments. At the end of every min and until the completion of the five-min task, the simulator emitted a beeping sound, signaling that it was time to begin the next maneuver in the task. Participants were also reminded of the specific maneuver to be performed at these times with the following keywords: “Ascend”, “Level off”, “Descend”, and “Level off”, respectively.

As all participants were novices at flying aircraft, crashes occurred. In such events, the simulator was programmed to resume the scenario at the starting altitude of 3000 ft heading due South at a speed of 180 knots. Throughout this restart procedure, the scenario’s timer kept running such that the entire scenario, including crashes, was maintained for 5 min. If the participant was informed of their next maneuver during a crash or while the scenario was reloading, the participant was instructed to begin the new maneuver once the scenario had resumed. At this time, the scenario continued as usual. Upon the completion of each scenario, participants completed the NASA TLX to provide their perceptions of task demand of the previously completed scenario (Hart & Staveland, 1988). During the first visit, all participants performed Scenario 1 followed by Scenario 2 while the order of scenarios was counter-balanced during visits 2 through 5. Performance data were acquired during all visits using a custom plug-in program collecting metrics such as altitude, airspeed, and heading. As visit 1 was primarily for introductory purposes, it was not included as part of the study design (Figure 6B).

During visits 2 to 5, EEG data were collected with a Brain Vision EEG system (Brain Products GmbH, Germany) using the BrainAmp Standard amplifier and 32 actiCAP active sensors arranged following the international 10-20 system (Jasper, 1958). The system was grounded at site AFz and was referenced to the left ear lobe; activity from the right ear lobe was also recorded for off-line re-referencing purposes. The EEG was recorded at a sampling rate of 1000 Hz (0.016 Hz online high-pass filter) and electrode impedances were kept below 10 kΩ throughout the experiment.

Data Processing

Behavioral performance and mental load surveys.

For each visit and task difficulty, the flight performance was assessed by computing the average speed and heading. Speed and heading (absolute error) were chosen as performance markers as they were the only metrics with a target value that remained constant throughout the task (target speed: 180 knots, target heading: due South, or 180 degrees). Also, for each level of difficulty, the scores for each subscale of the NASA-TLX were computed to evaluate the perceived mental workload.

EEG signal processing.

EEG data were processed using Brain Products Analyzer 2 software (Brain Products GmbH, Germany). First, the data were pruned to remove large movement artifacts and re-referenced to an averaged-ear montage. Next, the data were subjected to a bandpass filter (low-cutoff: 0.01Hz, high-cutoff: 55Hz, 48dB rolloff). Upon filtering, independent components analysis (ICA) was applied to remove ocular artifacts from the data by employing the ICA-based ocular artifact rejection function provided by the BrainVision Analyzer software. Independent components were defined relevant to vertical and horizontal ocular activity based upon the sum of squared correlations with the respective channels. The signal was then segmented in 1-s epochs, baseline corrected, and visually inspected for any remaining artifacts. Next, a Fast-Fourier Transform was applied to the epochs to extract the spectral composition using a Hamming window and 0.5-Hz bin sizes. All epochs were then averaged to obtain the spectral information for a given 5-min flight scenario. The data were then exported to Matlab (MathWorks Inc, USA) to calculate specific spectral power for the theta (4-7 Hz), low-alpha (8-10 Hz) and high-alpha (11-13 Hz) bandwidths. Moreover, the frontal theta / frontal alpha (FT/FA) and the frontal theta / parietal alpha (FT/PA) ratio power (scalp midline) were computed since both can robustly index changes in cognitive workload (Gentili et al., In press; Gentili et al., 2014; Hockey et al., 2009; Holm, Lukander, Korpela, Sallinen, & Müller, 2009; Postma et al., 2005). Spectral power data were then natural log-transformed prior to parametric statistical analysis. The same signal processing techniques were applied to the data for all visits and both levels of challenge.

Statistical Analysis

Performance, NASA-TLX scores and EEG measures.

Self-report data were subjected to a 4 x 2 (Difficulty x Visit) repeated-measures MANOVA including all six measures of the NASA TLX. A subsequent series of 4 x 2 (Difficulty x Visit) repeated measures ANOVAs was conducted for each dimension of the NASA TLX and, when needed, post-hoc analyses were conducted by employing the Tukey’s HSD test. A Greenhouse-Geisser correction was applied in the presence of violation of the sphericity assumption and corrected degrees of freedom are reported throughout. The same statistical analysis was applied to the two main performance metrics: airspeed and heading (for which the goal was to remain constant in terms of speed and heading).

The EEG data were subjected to a series of 2 Difficulty (Easy and Hard) x 4 Visit (V2, V3, V4, and V5) x 2 Hemisphere (Left, Right) x 5 Region (Frontal, Central, Temporal, parietal and Occipital) repeated measures ANOVAs for all frequency bands of interest (theta, low- and high-alpha). The theta/alpha ratios were subjected to 2 Difficulty (Easy and Hard) x 4 Visit (V2, V3, V4, and V5) repeated measures ANOVAs. When needed, post-hoc analyses were computed by employing using the Tukey's HSD test and the Greenhouse-Geisser correction was applied when the sphericity assumption was not met. For all statistics, the degrees of freedom of the p-values were corrected and partial eta squared (η_p^2) and Cohen's d effect sizes were also reported when appropriate. All criterion alpha levels were set to $p < 0.05$.

Predicting performance from prior EEG and NASA TLX measures.

We were also interested in the ability to predict performance (heading and speed) in a visit (visit n) based on EEG and NASA TLX recorded in the previous visit (n – 1). Thus, linear mixed-effect regressions were conducted. Specifically, we examined the predictive ability of any EEG or NASA TLX measure that exhibited a significant main effect of visit in the aforementioned analyses. Thus, we conducted two separate regressions for each predictor variable: one regression predicting speed in visit n and one regression predicting heading in visit n. In each regression, we controlled for the random effects of participants as well as the Participant x Visit and the Participant x Difficulty interactions. Further, we controlled for the fixed effects of difficulty, visit, and EEG/NASA TLX variable during current visit (visit n). The predictor of interest was the EEG/NASA TLX variable during the previous visit (visit n – 1). All criterion alpha levels were set to $p < 0.05$.

Results

Self-Report

As expected, MANOVA revealed significant omnibus main effects for both Visit ($F(18,240.9) = 3.545$, $p < 0.001$, $\eta_p^2 = 0.199$, Wilk's Lambda = 0.514) and Difficulty ($F(6,25) = 14.329$, $p < 0.001$, $\eta_p^2 = 0.775$, Wilk's Lambda = 0.225) for all six measures in the NASA TLX. Results for the individual subscales of the NASA TLX mirrored the omnibus results, indicating that participants perceived that i) task load decreased as the study progressed and ii) task load was lower in the easy compared to the hard condition, save for Physical Demand, which did not reveal an effect for visit (see Table 2, 3 and Figure 7). No significant Visit x Difficulty interaction was detected.

Table 2. Individual ANOVA results for self-report measures by employing the NASA TLX. The first, second, third fourth and fifth column represent the effect which is measured (here a main effect of Visit and Difficulty), the dimension of the NASA TLX, the obtained F-Value, p-value and partial η^2 effect size, respectively.

	Measure	F-ratio	P	Partial eta squared (η_p^2)
Visit	Mental Demand	F (3, 102) = 11.706	< 0.001	0.268
	Physical Demand	*F (3, 102) = 1.948*	*0.127*	*0.054*
	Temporal Demand	F (3, 102) = 7.669	< 0.001	0.184
	Performance	F (3, 102) = 18.486	< 0.001	0.352
	Effort	F (3, 102) = 6.081	0.002	0.152
	Frustration	F (3, 102) = 5.924	0.003	0.148
Difficulty	Mental Demand	F (1,34) = 88.242	< 0.001	0.734
	Physical Demand	F (1,34) = 62.895	< 0.001	0.649
	Temporal Demand	F (1,34) = 66.618	< 0.001	0.662
	Performance	F (1,34) = 23.538	< 0.001	0.409
	Effort	F (1,34) = 62.033	< 0.001	0.646
	Frustration	F (1,34) = 60.131	< 0.001	0.639

Table 3. Contrast between all visits (i.e., V1-V5) for each dimension of the NASA TLX. The first, second and third column represent the contrast of interest measured, the p-value and Cohen's d effect size, respectively. Findings that do not reach the significance threshold are italicized.

	Contrast	P	d		Contrast	P	d
Mental	V1 vs. V2	0.016	0.461	**Performance**	V1 vs. V2	0.003	0.586
	V1 vs. V3	0.001	0.675		V1 vs. V3	< 0.001	0.895
	V1 vs. V4	< 0.001	0.759		V1 vs. V4	< 0.001	0.962
	V2 vs. V3	0.006	0.529		V2 vs. V3	0.001	0.676
	V2 vs. V4	0.004	0.555		V2 vs. V4	< 0.001	0.730
	V3 vs. V4	*0.722*	*0.065*		*V3 vs. V4*	*0.721*	*-0.065*
Physical	*V1 vs. V2*	*0.538*	*0.112*	**Effort**	*V1 vs. V2*	*0.135*	*0.276*
	V1 vs. V3	0.043	0.380		V1 vs. V3	0.008	0.508
	V1 vs. V4	0.028	0.415		V1 vs. V4	0.004	0.558
	V2 vs. V3	0.045	0.375		V2 vs. V3	0.040	0.386
	V2 vs. V4	*0.059*	*0.353*		V2 vs. V4	0.009	0.505
	V3 vs. V4	*0.819*	*-0.041*		*V3 vs. V4*	*0.537*	*0.112*
Temporal	*V1 vs. V2*	*0.237*	*0.217*	**Frustration**	*V1 vs. V2*	*0.819*	*0.041*
	V1 vs. V3	0.001	0.631		V1 vs. V3	0.010	0.496
	V1 vs. V4	0.006	0.530		*V1 vs. V4*	*0.052*	*0.363*
	V2 vs. V3	0.002	0.599		V2 vs. V3	0.001	0.636
	V2 vs. V4	0.021	0.437		V2 vs. V4	0.003	0.585
	V3 vs. V4	*0.933*	*-0.015*		*V3 vs. V4*	*0.840*	*-0.036*

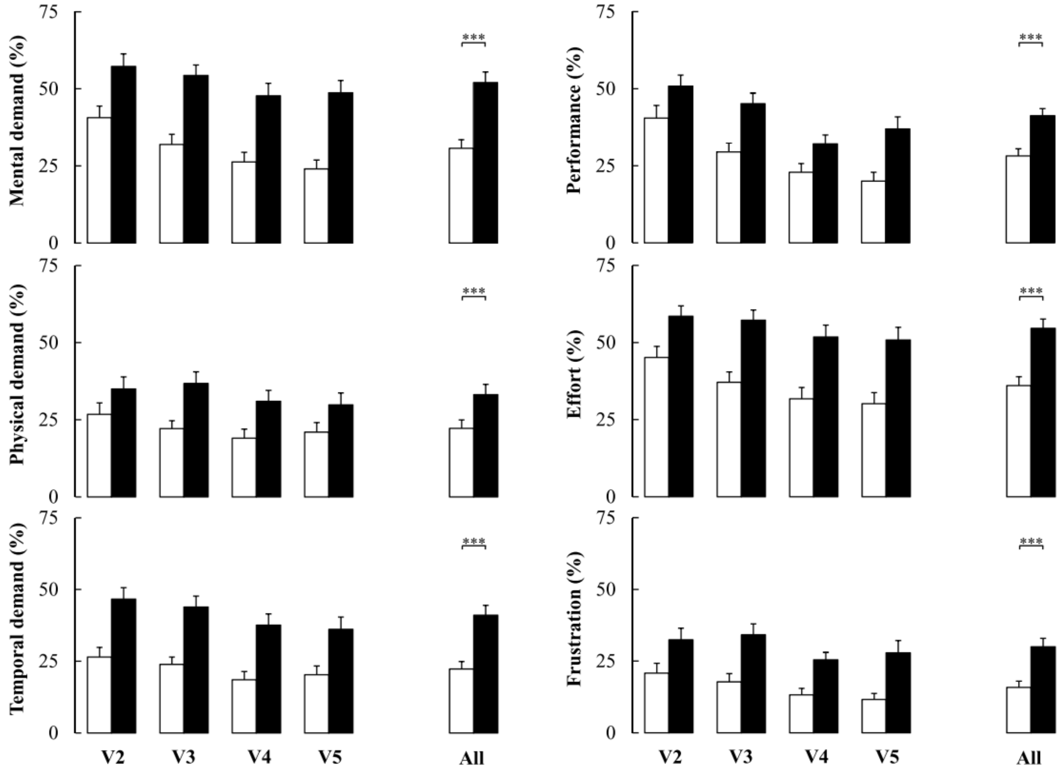

Figure 7. Variations of the self-report scores obtained for each dimension of the NASA TLX throughout practice during each visit (visit 2-5) while practicing under the easy (white bars) and hard (black bars) levels of difficulty.

Performance

As expected, MANOVA revealed significant omnibus main effects of Visit ($F(6,142) = 6.067$, $p < 0.001$, $\eta_p^2 = 0.204$, Wilk's Lambda = 0.634) and Difficulty ($F(2,23) = 5.884$, $p = 0.009$, $\eta_p^2 = 0.338$, Wilk's Lambda = 0.662) for both heading and airspeed. In subsequent application of ANOVAs, a main effect of Visit was observed for both heading ($F(3,72) = 6.494$, $p = 0.025$, $\eta_p^2 = 0.125$) and speed ($F(3,72) = 3.864$, $p = 0.002$, $\eta_p^2 = 0.178$) indicating that both measures of performance improved as the study progressed. Heading reached maximal performance at the third visit and stabilized, while speed reached maximal performance at the fourth visit and stabilized (see Table 4 for all the post-hoc contrasts for both heading and speed) (Figure 8). A main effect of difficulty for heading ($F(1,27) = 14.512$, $p = 0.001$, $\eta_p^2 = 0.350$) was also observed, such that participants were able to remain closer to their intended course during the easy condition relative to the hard condition.

Table 4. Contrast between the easy and hard task demand for the heading (second row) and the speed (third row) during flight performance. The first, second and third column represent the contrast of interest measured, the p-value and Cohen's d effect size, respectively. Findings that do not reach the significance threshold are italicized.

	Contrast	**P**	**d**
Heading	V1 vs. V2	0.017	0.516
	V1 vs. V3	0.019	0.503
	V1 vs. V4	0.011	0.548
	V2 vs. V3	*0.876*	*-0.031*
	V2 vs. V4	*0.968*	*-0.008*
	V3 vs. V4	*0.885*	*0.029*
Speed	*V1 vs. V2*	*0.752*	*-0.064*
	V1 vs. V3	0.005	0.624
	V1 vs. V4	0.029	0.464
	V2 vs. V3	0.001	0.796
	V2 vs. V4	0.002	0.715
	V3 vs. V4	*0.172*	*-0.281*

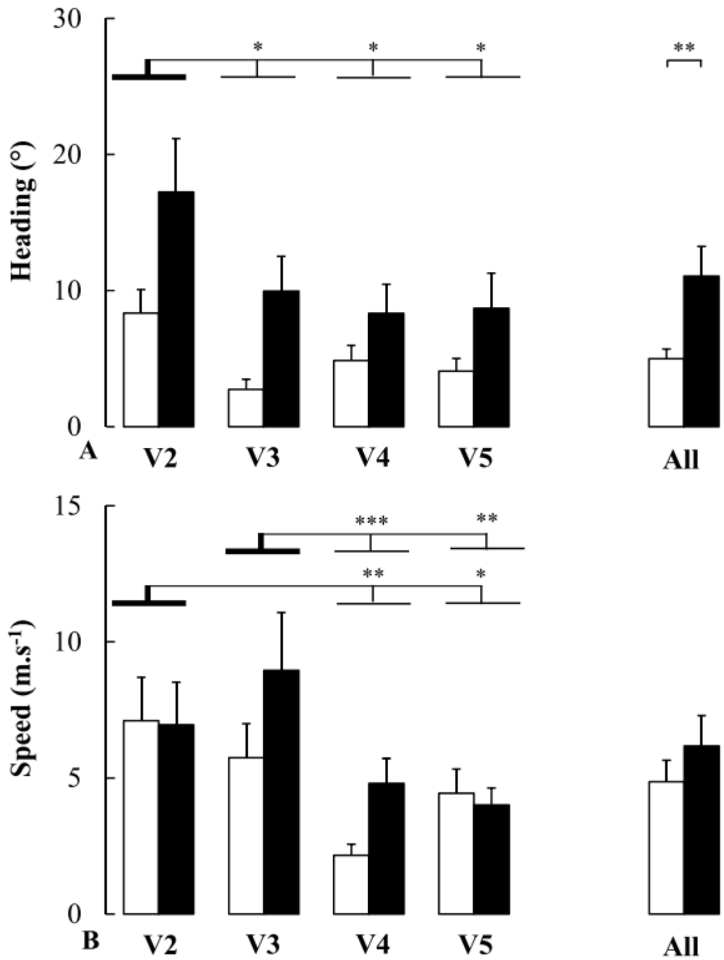

Figure 8. Change in behavioral performance of the participants while practicing the flight task performance during the training sessions for each of the visits #2 to #5 under an easy (white bars) and hard (black bars) level of difficulty. The grand average computed for the absolute error for heading (first row) and speed (second row) across the practice session (i.e., across visits 2-5) during the easy (white bars) and hard (black bars) task demand are represented on the right within each panel. The thick part of the fork represent the values which is used as a reference and compared to other values. V: Visit. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

EEG

Theta

As predicted, the results revealed a main effect for Visit ($F(3,102) = 3.520$, $p = 0.018$, $\eta_p^2 = 0.094$). Post-hoc analyses revealed that the theta power was lower during the first compared to the last learning session (i.e., V2 < V5; $p = 0.008$, $d = 0.176$). Contrary to expectation, there were no effects for Difficulty despite directional trends for theta to be larger in the hard compared to the easy condition. No other relevant main effects or interactions were observed (Figure 9, top row).

Low-alpha power

Main effects were revealed for both Visit ($F(3,102) = 4.749$, $p = 0.004$, $\eta_p^2 = 0.123$) and Region ($F(4,136) = 36.845$, $p < 0.001$, $\eta_p^2 = 0.520$). However, those were superseded by a significant Visit x Region interaction ($F(12,408) = 3.209$, $p = 0.008$, $\eta_p^2 = 0.086$). Post-hoc analyses revealed that low-alpha power in the temporal region was lower during visit 2 compared to other visits (V2 < V3, $p < 0.001$, $d = 0.287$; V2 < V4, $p < 0.001$, $d = 0.310$ and V2 < V5, $p < 0.001$, $d = 0.347$) (Figure 9, middle row). A Difficulty x Hemisphere interaction was also observed ($F(1,34) = 4.356$, $p = 0.044$, $\eta_p^2 = 0.114$)such that attenuated low-alpha power was observed for the left hemisphere when the task difficulty increased (Easy < Hard, $p = 0.001$, $d = 0.091$), whereas no such difference was observed for the right hemisphere. No other main effects or interactions of interest were identified.

High-alpha power

A main effect for Difficulty ($F(1,34) = 26.679$, $p < 0.001$, $\eta_p^2 = 0.440$) was revealed indicative of elevated high-alpha power during the easy condition relative to the hard condition. In addition, main effects were also revealed for both Visit ($F(3,102) = 5.391$, $p = 0.002$, $\eta_p^2 = 0.137$) and Region ($F(4,136) = 5.080$, $p < 0.001$, $\eta_p^2 = 0.402$). However, those were superseded by a Visit x Region interaction ($F(12,408) = 7.342$, $p = 0.013$, $\eta_p^2 = 0.076$). Post-hoc analyses revealed that high-alpha power increased across visits in the central (V2 < V5: $p = 0.017$, $d = 0.210$), temporal (V2 < V3: $p < 0.001$, $d = 0.257$; V2 < V4: $p < 0.001$, $d = 0.274$; V2 < V5: $p < 0.001$, $d = 0.273$), parietal (V2 < V4: $p = 0.007$, $d = 0.245$; V2 < V5: $p = 0. 003$, $d = 0.245$), and occipital (V2 < V4: $p = 0.066$, $d = 0.255$; V2 < V5: $p = 0.038$, $d = 0.251$) regions; no such change was observed in the frontal region. No other main effects or interactions of interest were detected (Figure 9, bottom row).

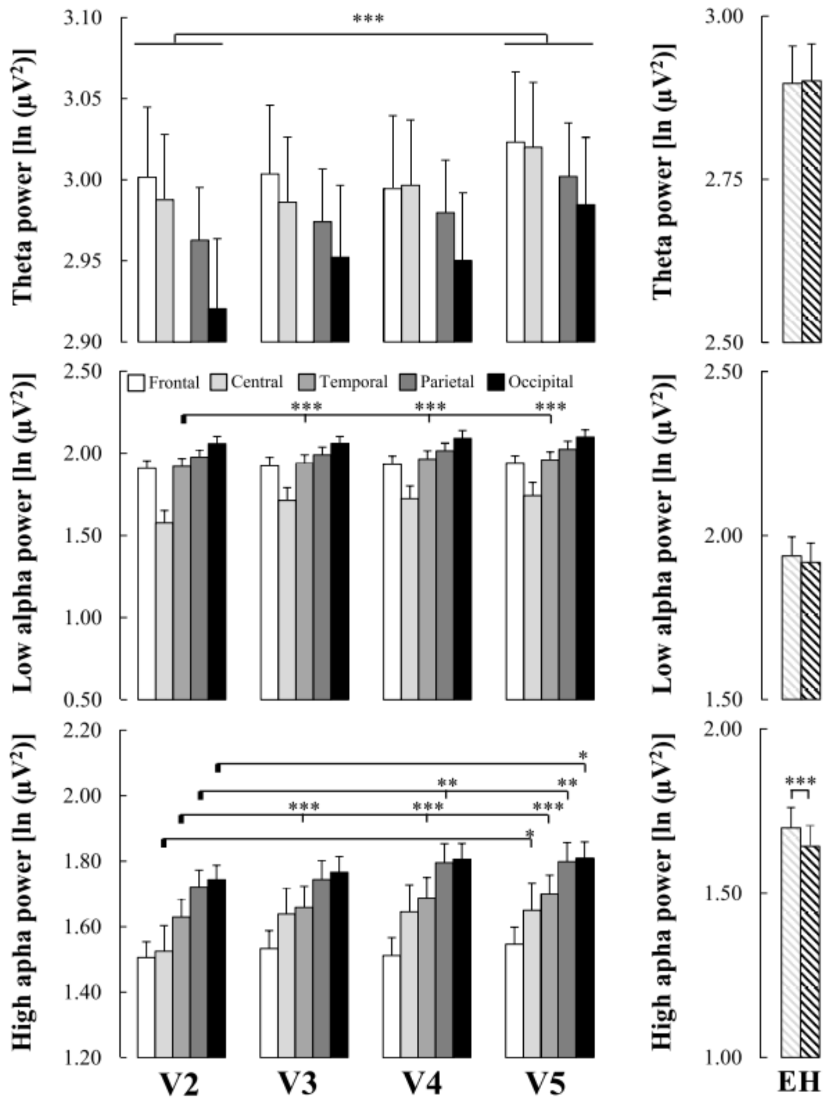

Figure 9. Changes in EEG spectral power throughout the four practice sessions (i.e., visits 2-5) for the frontal, central, temporal, parietal and occipital regions and both levels of task difficulty. The average power computed for each frequency band across all practice session (i.e., visits 2-5) during the easy (white bars) and hard (black bars) level of task demand are represented on the right within each panel. V: Visit. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

Theta / alpha power ratio

As expected, a main effect of Difficulty was revealed for both the frontal-theta/frontal-alpha ratios ($F(1,34) = 4.282$, $p = 0.046$, $\eta_p^2 = 0.112$; Figure 10, top row) and the frontal-theta/parietal-alpha ratio ($F(1, 34) = 9.885$, $p = 0.003$, $\eta_p^2 = 0.225$; Figure 10, bottom row), such that the theta/alpha ratio was elevated during the hard condition relative to the easy condition. No other main effects or interactions of interest were detected.

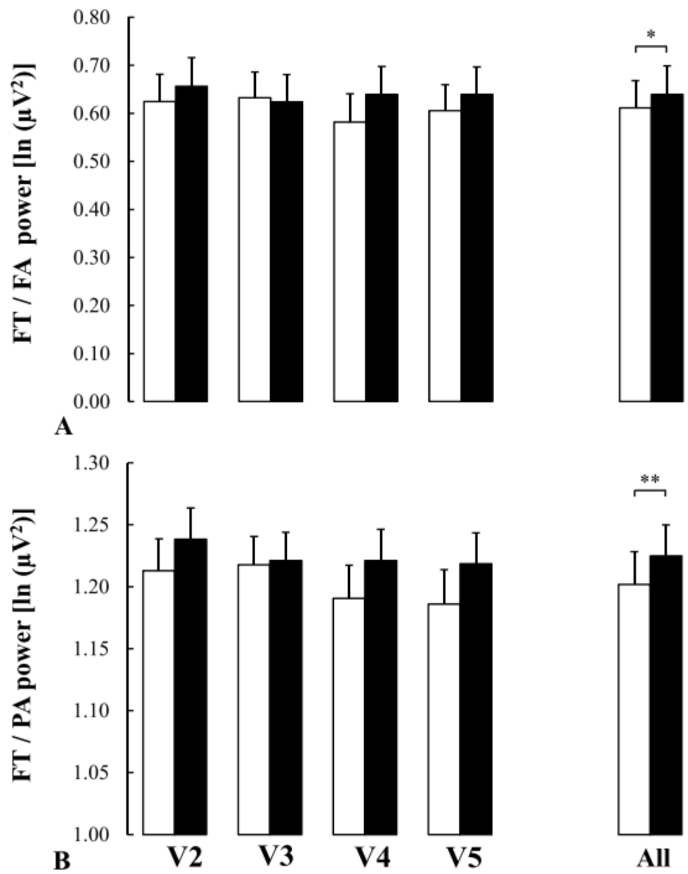

Figure 10. EEG spectral power ratios for the frontal and parietal regions as a result of practice and task demand. Frontal theta/frontal alpha (top row) and frontal theta/parietal alpha (bottom row) power ratio during practice (i.e., visit 2-5) under easy (white bars) and hard (black bars) task difficulty. The average frontal theta/frontal alpha (top row) and frontal theta/parietal alpha (bottom row) computed across all practice sessions (i.e., visit 2-5) under an easy (white bars) and hard (black bars) task difficulty are represented

on the right within each panel. V: Visit. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

Predicting performance from prior EEG and NASA-TLX measures

Only one of the linear mixed-effect regressions revealed a significant result. Specifically, high-alpha power recorded during the previous visit predicted heading in the current visit (slope = 17.1, $p = 0.032$). This effect demonstrated that greater high-alpha power during the previous visit was associated with more heading error during the current visit.

Discussion

In this study, we investigated the brain dynamics related to mental workload via EEG during the practice of a novel and complex cognitive-motor task under two levels of difficulty across multiple visits. First, regarding task performance, we observed expected improvements with practice time (i.e., visits) and detriments with increases in task difficulty. We also observed the expected reductions in perceived task demand with practice, while the perception of task demand increased with task difficulty. These findings provide a measure of confidence in the study manipulation in that the participants appeared to have learned the task to some degree and were subjectively sensitive to changes in task difficulty.

Our EEG results broadly replicated and extended previous work illustrating that both theta and alpha power increase with skill acquisition while alpha power was negatively related to task difficulty. However, we did not observe interactions between practice and difficulty. The following sections will discuss these findings in detail.

Theta power

We observed the expected effects of learning such that theta power increased over the practice sessions, which is consistent with previous learning studies that revealed similar directional changes in theta power, particularly in the frontal regions (Caplan et al., 2003; Perfetti et al., 2011; Smith et al., 1999; Tombini et al., 2009). Synchrony of frontal theta power may indicate an intensified recruitment of central executive functions (e.g., working memory and attention) (Cheng, Hung, et al., 2015; Klimesch, 1999; Sauseng, Griesmayr, Freunberger, & Klimesch, 2010; Slobounov, Ray, Johnson, Slobounov, & Newell, 2015; Slobounov, Teel, & Newell, 2013). As learning progresses and performance improves, individuals become increasingly effective at extracting and processing relevant information from the task environment and engaging their cognitive resources. Thus, the positive relationship observed between theta synchrony and learning may reflect elevated recruitment of attentional and working memory resources as individuals become more proficient as a result of learning (Gevins et al., 1997; Warm, Dember, & Hancock, 1996). Similarly, theta power has also been related to action monitoring, which could be increased when participants become more aware of the proper actions to take as a function of learning (Weber & Doppelmayr, 2016).

Surprisingly, however, we did not observe a positive relationship between task difficulty and EEG theta synchrony although prior work revealed that theta power tends to increase with task difficulty (Brookings et al., 1996; Rietschel et al., 2012). It is possible that the flight simulator task employed here was more complex compared to others utilized in the literature. Perhaps the challenging nature of the flight task, regardless of the condition, was so demanding that it induced a similar (i.e., maximal or close to maximal) recruitment of executive processes from which further immediate increases would be limited. This explanation may also be a reason for the lack of the expected interaction between practice and task difficulty for frontal theta, suggesting that the recruitment of executive resources for both levels of difficulty was similar throughout all practice sessions. A simpler experimental task should be used in future work.

Alpha power

We observed the expected effect of learning for high-alpha power recorded broadly over the scalp. This finding is consistent with other findings in the literature relating high-alpha synchrony with decreased recruitment of cognitive processes required for task performance, and with decreased mental workload (Gentili et al., 2011; Gevins & Smith, 2003; Gevins et al., 1997; Jaiswal et al., 2010). High-alpha synchrony in frontal and parietal regions has been related to inhibition ofof non-essential stimuli, and inhibition of multimodal sensory processing of such stimuli (Jensen & Mazaheri, 2010), in accordance with one's level of proficiency (Kerick et al., 2004; Landers et al., 1994). Given that high-alpha power exhibited no change in the frontal executive regions across the practice sessions, it may be that those executive processes remained engaged throughout practice, which is consistent with the results for theta power. Due to the complexity of the task, it may be that the amount of practice performed during the present experiment was too short and limited the reduction of explicit executive control functions, as typically occurs during skilled performance and with automaticity. It is likely that further practice is needed to reduce the activation of these frontal executive regions. Learning effects for low-alpha power, related to general cortical arousal as opposed to task-specific processes, were isolated to the temporal regions (Budzynski et al., 2009; Haufler et al., 2000). As such, it appears that learning modulated task-specific cognitive processing more so than general arousal.

As expected, we also observed an inverse relationship between task difficulty and high-alpha power. Specifically, as the task difficulty increased, high-alpha power was reduced across all cortical regions. This finding suggests an elevation of of task-related cortical activity with greater challenge, which was likely required to meet increasing task demands and is consistent with other findings reported in the literature (Gentili et al., 2014; Gevins et al., 1997; Jaquess et al., 2017; Rietschel et al., 2012). The lack of change in low-alpha power once again indicates that it was less sensitive to task-related changes than high-alpha power and that the participants were similarly aroused during the tasks.

Unexpectedly, we did not observe any interaction between practice and task difficulty for either low- or high-alpha power, which may indicate that cortical processes were refined in a similar manner during learning for both levels of difficulty. Given arguments that alpha power is indicative of inhibitory processes (Klimesch, Sauseng, & Hanslmayr, 2007), it may be that the temporal dynamics of those inhibitory mechanisms are not highly dependent upon task demands, specifically task difficulty, suggesting a relatively robust system.

Theta/Alpha Power Ratio

As an exploratory question, we investigated how the ratio of theta to alpha power was modulated by learning under varying levels of task difficulty. Conceptually, a ratio of theta/alpha would normalize working memory and attention engagement to one's level of cortical activation and arousal, which may be a more effective indicator of mental workload than absolute theta or alpha. Indeed, the theta/alpha ratio increases with task difficulty (Gentili et al., 2014; Holm et al., 2009; Jaquess et al., 2017; Shaw et al., In press). In the present experiment, the theta/alpha ratio, at all locations measured (i.e., frontal theta/frontal alpha and frontal theta/parietal alpha), displayed a positive relationship with task difficulty, supportive of previous work.

No effects of learning were observed despite a trend that the theta/alpha ratio diminished with practice, nor was there an interaction between practice and difficulty. The lack of any significant change in the ratio over the practice sessions is reasonable from a measurement perspective given that theta and alpha power both increased during learning. That said, further understanding of the temporal dynamics of theta and alpha and the associated neuro-cognitive processes may be beneficial to understanding their related contributions to changes in mental workload during learning.

Exploratory Predictive Analysis

With respect to the prediction of performance from cortical dynamics and self-reported mental workload during an earlier phase of practice, the linear mixed-effect regression analyses revealed that heading errors during a current training visit were predicted by high-alpha power during the previous training visit. This result suggests that lack of attentional engagement was related to poor subsequent performance or, from a different perspective, that greater cortical activation (i.e., reduced high-alpha power) during a training visit promotes superior heading performance. This finding is in agreement with the theoretical notion that greater investment or engagement of attention resources during practice allows for improved learning and retention (Sweller, 2010; Van Merrienboer & Sweller, 2005).

Conclusion and Future Directions

Overall, the results of this investigation confirm and extend previous work from both performance and learning domains by suggesting that i) the brain "works harder" under more difficult learning conditions, and ii) brain adaptations over multiple practice sessions are characterized by refinement of the neuro-cognitive processes involved in task performance and are in agreement with the achievement of neural efficiency. To our knowledge, only two other EEG studies investigated brain dynamics during cognitive-motor skill learning over multiple visits (Kerick et al., 2004; Landers et al., 1994). More importantly, however, by investigating practice and task difficulty in an interactive manner from a cortical dynamics perspective, we observed that individuals learn at similar rates across two levels of demand under complex task conditions; no interaction between task difficulty and practice for any of the EEG measures was observed. Such a lack of interaction is of interest as it is often speculated that certain levels of difficulty would lead to improved rates of learning or performance (Akizuki & Ohashi, 2015; Guadagnoli & Lee, 2004; Shuggi, Oh, et al., 2017). The absence of such an interaction implies that the refinement of relevant neural processes of mental workload (as indicated by alpha and theta synchrony) occurred at a similar rate throughout learning for both levels of task difficulty, at least for the duration of practice examined.

Prior work revealed that under levels of “optimal challenge,” achieved by manipulating task difficulty to individually-ideal levels, individuals tend to learn better than under less-optimal levels of challenge (Akizuki & Ohashi, 2015) as predicted by the challenge point framework (Guadagnoli & Lee, 2004). However, the present lack of an observed interaction between practice time and task difficulty in either performance improvement or cortical dynamics in this study implies that both change similarly regardless of level of difficulty under complex task conditions. If this finding is interpreted under the challenge point framework, it may indicate that this window of optimal challenge may be relatively limited. Future studies may consider utilizing more varied levels of difficulty to provide a richer landscape from which to infer appropriate levels of workload for improved practice effectiveness. Alternatively, self-control of task difficulty may be a valid method with which to identify individually-appropriate levels of difficulty, given findings that self-controlled practice can lead to better learning outcomes than externally-imposed practice (Andrieux, Boutin, & Thon, 2016; Andrieux, Danna, & Thon, 2012; Leiker et al., 2016; Wu & Magill, 2011). This notion implies that learners practicing in self-controlled conditions are practicing at a level at or near their optimal challenge point. Future work employing both EEG and behavioral measures could be used to further investigate the neurocognitive mechanisms underlying self-control of task difficulty during practice.

References

Akizuki, K., & Ohashi, Y. (2015). Measurement of functional task difficulty during motor learning: What level of difficulty corresponds to the optimal challenge point? Human Movement Science, 43, 107-117.

Andrieux, M., Boutin, A., & Thon, B. (2016). Self-control of task difficulty during early practice promotes motor skill learning. Journal of Motor Behavior, 48(1), 57-65.

Andrieux, M., Danna, J., & Thon, B. (2012). Self-control of task difficulty during training enhances motor learning of a complex coincidence-anticipation task. Research Quarterly for Exercise and Sport, 83(1), 27-35.

Ayaz, H., Shewokis, P. A., Bunce, S., Izzetoglu, K., Willems, B., & Onaral, B. (2012). Optical brain monitoring for operator training and mental workload assessment. Neuroimage, 59(1), 36-47.

Ayaz, H., Willems, B., Bunce, B., Shewokis, P. A., Izzetoglu, K., Hah, S., . . . Onaral, B. (2010). Cognitive workload assessment of air traffic controllers using optical brain imaging sensors. Advances in understanding human performance: Neuroergonomics, Human Factors Design, and Special Populations, 21-31.

Boutin, A., Badets, A., Salesse, R. N., Fries, U., Panzer, S., & Blandin, Y. (2012). Practice makes transfer of motor skills imperfect. Psychological Research, 76(5), 611-625.

Boutin, A., Blandin, Y., Massen, C., Heuer, H., & Badets, A. (2014). Conscious awareness of action potentiates sensorimotor learning. Cognition, 133(1), 1-9.

Boutin, A., Panzer, S., & Blandin, Y. (2013). Retrieval practice in motor learning. Human Movement Science, 32(6), 1201-1213.

Boutin, A., Pinsard, B., Boré, A., Carrier, J., Fogel, S. M., & Doyon, J. (2017). Transient synchronization of hippocampo-striato-thalamo-cortical networks during sleep spindle oscillations induces motor memory consolidation. Neuroimage.

Brookings, J. B., Wilson, G. F., & Swain, C. R. (1996). Psychophysiological responses to changes in workload during simulated air traffic control. Biological Psychology, 42(3), 361-377.

Budzynski, T. H., Budzynski, H. K., Evans, J. R., & Abarbanel, A. (2009). Introduction to quantitative EEG and neurofeedback: Advanced theory and applications: Academic Press.

Caplan, J. B., Madsen, J. R., Schulze-Bonhage, A., Aschenbrenner-Scheibe, R., Newman, E. L., & Kahana, M. J. (2003). Human θ oscillations related to sensorimotor integration and spatial learning. Journal of Neuroscience, 23(11), 4726-4736.

Cheng, M.-Y., Huang, C.-J., Chang, Y.-K., Koester, D., Schack, T., & Hung, T.-M. (2015). Sensorimotor rhythm neurofeedback enhances golf putting performance. Journal of Sport and Exercise Psychology, 37(6), 626-636.

Cheng, M.-Y., Hung, C.-L., Huang, C.-J., Chang, Y.-K., Lo, L.-C., Shen, C., & Hung, T.-M. (2015). Expert-novice differences in SMR activity during dart throwing. Biological Psychology, 110, 212-218.

Gentili, R. J., Bradberry, T. J., Oh, H., Hatfield, B. D., & Contreras Vidal, J. L.

(2011). Cerebral cortical dynamics during visuomotor transformation: Adaptation to a cognitive-motor executive challenge. Psychophysiology, 48(6), 813-824.

Gentili, R. J., Jaquess, K. J., Shuggi, I. M., Shaw, E. P., Oh, H., Lo, L. C., . . . Hatfield, B. D. (In press). Combined assessment of attentional reserve and cognitive-motor effort under various levels of challenge with a dry EEG system. Psychophysiology.

Gentili, R. J., Rietschel, J. C., Jaquess, K. J., Lo, L.-C., Prevost, M., Miller, M. W., . . . Hatfield, B. D. (2014). Brain biomarkers based assessment of cognitive workload in pilots under various task demands. Paper presented at the Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE.

Gentili, R. J., Shewokis, P. A., Ayaz, H., & Contreras-Vidal, J. L. (2013). Functional near-infrared spectroscopy-based correlates of prefrontal cortical dynamics during a cognitive-motor executive adaptation task. Frontiers in Human Neuroscience, 7.

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. Theoretical Issues in Ergonomics Science, 4(1-2), 113-131.

Gevins, A., Smith, M. E., McEvoy, L., & Yu, D. (1997). High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. Cerebral Cortex, 7(4), 374-385.

Guadagnoli, M. A., & Lee, T. D. (2004). Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. Journal of Motor Behavior, 36(2), 212-224.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in Psychology, 52, 139-183.

Haufler, A. J., Spalding, T. W., Santa Maria, D., & Hatfield, B. D. (2000). Neuro-cognitive activity during a self-paced visuospatial task: comparative EEG profiles in marksmen and novice shooters. Biological Psychology, 53(2), 131-160.

Herholz, S. C., & Zatorre, R. J. (2012). Musical training as a framework for brain plasticity: behavior, function, and structure. Neuron, 76(3), 486-502.

Hockey, G. R. J., Nickel, P., Roberts, A. C., & Roberts, M. H. (2009). Sensitivity of candidate markers of psychophysiological strain to cyclical changes in manual control load during simulated process control. Applied Ergonomics, 40(6), 1011-1018.

Holm, A., Lukander, K., Korpela, J., Sallinen, M., & Müller, K. M. (2009). Estimating brain load from the EEG. The Scientific World Journal, 9, 639-651.

Jaiswal, N., Ray, W., & Slobounov, S. (2010). Encoding of visual–spatial information in working memory requires more cerebral efforts than retrieval: Evidence from an EEG and virtual reality study. Brain Research, 1347, 80-89.

Jaquess, K. J., Gentili, R. J., Lo, L. C., Oh, H., Zhang, J., Rietschel, J. C., . . . Hatfield, B. D. (2017). Empirical evidence for the relationship between cognitive workload and attentional reserve. . International Journal of Psychophysiology, 121, 46-55.

Jasper, H. H. (1958). Report of the committee on methods of clinical examination in electroencephalography. Electroencephalography and Clinical Neurophysiology, 10(2), 370-375. doi: http://dx.doi.org/10.1016/0013-4694(58)90053-1

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. Frontiers in Human Neuroscience, 4, 186.

Kantak, S. S., & Winstein, C. J. (2012). Learning–performance distinction and memory processes for motor skills: A focused review and perspective. Behavioural Brain Research, 228(1), 219-231.

Kantowitz, B. H. (1987). 3. Mental Workload. Advances in psychology, 47, 81-121.

Kerick, S. E., Douglass, L. W., & Hatfield, B. D. (2004). Cerebral cortical adaptations associated with visuomotor practice. Medicine & Science in Sports & Exercise, 36(1), 118-129.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain research reviews, 29(2–3), 169-195. doi: http://dx.doi.org/10.1016/S0165-0173(98)00056-3

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: the inhibition–timing hypothesis. Brain Research Reviews, 53(1), 63-88.

Krakauer, J. W., & Mazzoni, P. (2011). Human sensorimotor learning: adaptation, skill, and beyond. Current Opinion in Neurobiology, 21(4), 636-644.

Landers, D. M., Han, M., Salazar, W., & Petruzzello, S. J. (1994). Effects of learning on electroencephalographic and electrocardiographic patterns in novice archers. International Journal of Sport Psychology.

Leiker, A. M., Bruzi, A. T., Miller, M. W., Nelson, M., Wegman, R., & Lohse, K. R. (2016). The effects of autonomous difficulty selection on engagement, motivation, and learning in a motion-controlled video game task. Human Movement Science, 49, 326-335.

Magill, R. A., & Anderson, D. (2016). Motor Learning and Control: Concepts and Applications (11 ed.). New York: McGraw-Hill Education.

Marteniuk, R. G. (1976). Information processing in motor skills: Holt, Rinehart and Winston.

Nassef, A., Mahfouf, M., Linkens, D., Elsamahy, E., Roberts, A., Nickel, P., . . . Panoutsos, G. (2009). The assessment of Heart Rate Variability (HRV) and Task Load Index (TLI) as physiological markers for physical stress. Paper presented at the World Congress on Medical Physics and Biomedical Engineering, September 7-12, 2009, Munich, Germany.

Palinko, O., Kun, A. L., Shyrokov, A., & Heeman, P. (2010). Estimating cognitive load using remote eye tracking in a driving simulator. Paper presented at the Proceedings of the 2010 Symposium on Eye-Tracking Research & Applications.

Perfetti, B., Moisello, C., Landsness, E. C., Kvint, S., Lanzafame, S., Onofrj, M., . . . Ghilardi, M. F. (2011). Modulation of gamma and theta spectral amplitude and phase synchronization is associated with the development of visuo-motor learning. Journal of Neuroscience, 31(41), 14810-14819.

Postma, M. A., Schellekens, J., Hanson, E. K., & Hoogeboom, P. J. (2005). Fz theta divided by Pz alpha as an index of task load during a PC-based air traffic control simulation (pp. 1-5): Shaker Publishing, Maastricht, The Netherlands.

Rietschel, J. C., McDonald, C. G., Goodman, R. N., Miller, M. W., Jones-Lush, L. M., Wittenberg, G. F., & Hatfield, B. D. (2014). Psychophysiological support of increasing attentional reserve during the development of a motor skill. Biological Psychology, 103, 349-356.

Rietschel, J. C., Miller, M. W., Gentili, R. J., Goodman, R. N., McDonald, C. G., & Hatfield, B. D. (2012). Cerebral-cortical networking and activation increase as a function of cognitive-motor task difficulty. Biological Psychology, 90(2), 127-133. doi: http://dx.doi.org/10.1016/j.biopsycho.2012.02.022

Sauseng, P., Griesmayr, B., Freunberger, R., & Klimesch, W. (2010). Control mechanisms in working memory: a possible function of EEG theta oscillations. Neuroscience & Biobehavioral Reviews, 34(7), 1015-1022.

Seidler, R. D., Bo, J., & Anguera, J. A. (2012). Neurocognitive contributions to motor skill learning: the role of working memory. Journal of Motor Behavior, 44(6), 445-453.

Shadmehr, R., & Wise, S. P. (2005). The computational neurobiology of reaching and pointing: a foundation for motor learning: MIT press.

Shaw, E. P., Rietschel, J. C., Hendershot, B. D., Pruziner, A. L., Miller, M. W., Hatfield, B. D., & Gentili, R. J. (In press). Measurement of attentional reserve and mental effort for cognitive workload assessment under various task demands during dual-task walking. Biological Psychology.

Shewokis, P. A., Ayaz, H., Panait, L., Liu, Y., Syed, M., Greenawald, L., . . . Lind, D. S. (2015). Brain-in-the-Loop learning using fNIR and simulated virtual reality surgical tasks: hemodynamic and behavioral effects. Paper presented at the International Conference on Augmented Cognition.

Shewokis, P. A., Shariff, F. U., Liu, Y., Ayaz, H., Castellanos, A., & Lind, D. S. (2017). Acquisition, retention and transfer of simulated laparoscopic tasks using fNIR and a contextual interference paradigm. The American Journal of Surgery, 213(2), 336-345.

Shuggi, I. M., Oh, H., Shewokis, P. A., & Gentili, R. J. (2017). Mental workload and motor performance dynamics during practice of reaching movements under various levels of task difficulty. Neuroscience, 360, 166-179.

Shuggi, I. M., Shewokis, P. A., Herrmann, J. W., & Gentili, R. J. (2017). Changes in motor performance and mental workload during practice of reaching movements: a team dynamics perspective. Experimental Brain Research, 1-19.

Slobounov, S. M., Ray, W., Johnson, B., Slobounov, E., & Newell, K. M. (2015). Modulation of cortical activity in 2D versus 3D virtual reality environments: an EEG study. International Journal of Psychophysiology, 95(3), 254-260.

Slobounov, S. M., Teel, E., & Newell, K. M. (2013). Modulation of cortical activity in response to visually induced postural perturbation: combined VR and EEG study. Neuroscience Letters, 547, 6-9.

Smith, M. E., McEvoy, L. K., & Gevins, A. (1999). Neurophysiological indices of strategy development and skill acquisition. Cognitive Brain Research, 7(3), 389-404.

Svensson, E., Angelborg-Thanderez, M., Sjöberg, L., & Olsson, S. (1997). Information complexity-mental workload and performance in combat aircraft. Ergonomics, 40(3), 362-380.

Sweller, J. (2010). Element Interactivity and Intrinsic, Extraneous, and Germane Cognitive Load. Educational psychology review, 22(2), 123-138. doi: 10.1007/s10648-010-9128-5

Tombini, M., Zappasodi, F., Zollo, L., Pellegrino, G., Cavallo, G., Tecchio, F., . . . Rossini, P. M. (2009). Brain activity preceding a 2D manual catching task. Neuroimage, 47(4), 1735-1746.

Van Merrienboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. Educational Psychology Review, 17(2), 147-177.

Warm, J. S., Dember, W. N., & Hancock, P. A. (1996). Vigilance and workload in automated systems. In R. Parasuraman & M. Mouloua (Eds.), Automation and human performance: Theory and applications (pp. 183-200). Hillsdale, N.J.: Lawrence Erlbaum Associates.

Weber, E., & Doppelmayr, M. (2016). Kinesthetic motor imagery training modulates frontal midline theta during imagination of a dart throw. International Journal of Psychophysiology, 110, 137-145.

Wu, W. F., & Magill, R. A. (2011). Allowing learners to choose: self-controlled practice schedules for learning multiple movement patterns. Research Quarterly for Exercise and Sport, 82(3), 449-457.

Chapter 5: Transition from Study 2 and Study 3

The above study (Jaquess et al., Under revision) replicated and extended previous work by illustrating that, when an individual is challenged by a cognitive-motor task, his/her mental workload increases, as indicated by EEG spectral measures of cortical activation. Furthermore, as an individual acquires a cognitive-motor skill through practice (i.e., the skill becomes more learned), mental workload, and cortical activation, decrease. Interestingly, it was observed that this refinement of cortical activity due to learning occurred at a similar rate regardless of task difficulty.

Based upon various theories of skill acquisition (Guadagnoli & Lee, 2004; Sweller, 1988, 2010), it was expected that the rate of learning would be impacted by task difficulty. More specifically, it would be expected that tasks of moderate difficulty would be related to improved learning outcomes relative to excessively easy or excessively hard tasks. One potential reason this was not observed would be that, given that the task (i.e., operating a flight simulator) was so complex, the difference in difficulty between the relatively easy and hard conditions was not large enough. In other words, even the easy task was still quite difficult, perhaps excessively so for the novice sample that was used to be considered “easy”. To move forward, it would be prudent 1) use a less complex task and 2) to utilize a more effective manipulation of task difficulty that is more sensitive to the participant’s level of skill.

To address the first point, the next experiment utilized a golf putting task. While golf putting may be considered a gross motor task as opposed to the relatively fine movements of manipulating a joystick, it can be considered less complex than the flight simulator (i.e., there are fewer explicit pieces of information to monitor) with a simpler goal (i.e., hit the ball to the target) while still retaining ecological validity.

To address the second point, a method of practice known as self-controlled practice was employed, which allows individuals to manipulate certain aspects of their practice environment, including access to feedback (Chiviacowsky & Wulf, 2002; Janelle, Kim, & Singer, 1995), the usage of demonstration (Wulf, Raupach, & Pfeiffer, 2005) and assistive devices (Hartman, 2007; Wulf & Toole, 1999), or, as used in the following study, task difficulty (Andrieux, Boutin, & Thon, 2016; Andrieux, Danna, & Thon, 2012). Self-controlled practice promotes task engagement (Wulf, 2007) and allows learners to challenge themselves in an individually-appropriate way relative to more traditional externally-controlled practice methods, which may be too hard or too easy to most effectively promote learning. The following experiment will examine to effectiveness of self-controlled practice as a practice methodology and its ability to impact cortical dynamics during cognitive-motor skill learning and subsequent performance.

References

Andrieux, M., Boutin, A., & Thon, B. (2016). Self-control of task difficulty during early practice promotes motor skill learning. Journal of Motor Behavior, 48(1), 57-65.

Andrieux, M., Danna, J., & Thon, B. (2012). Self-control of task difficulty during training enhances motor learning of a complex coincidence-anticipation task. Research Quarterly for Exercise and Sport, 83(1), 27-35.

Chiviacowsky, S., & Wulf, G. (2002). Self-controlled feedback: Does it enhance learning because performers get feedback when they need it? Research Quarterly for Exercise and Sport, 73(4), 408-415.

Guadagnoli, M. A., & Lee, T. D. (2004). Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. Journal of Motor Behavior, 36(2), 212-224.

Hartman, J. M. (2007). Self-controlled use of a perceived physical assistance device during a balancing task. Perceptual and Motor Skills, 104(3), 1005-1016.

Janelle, C. M., Kim, J., & Singer, R. N. (1995). Subject-controlled performance feedback and learning of a closed motor skill. Perceptual and Motor Skills, 81(2), 627-634.

Jaquess, K. J., Lo, L. C., Oh, H., Lu, C., Ginsberg, A., Tan, Y. Y., . . . Gentili, R. J. (Under revision). Changes in mental workload and motor performance throughout multiple practice sessions under various levels of task difficulty. Neuroscience.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12(2), 257-285. doi: http://dx.doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2010). Element Interactivity and Intrinsic, Extraneous, and Germane Cognitive Load. Educational Psychology Review, 22(2), 123-138. doi: 10.1007/s10648-010-9128-5

Wulf, G. (2007). Self-controlled practice enhances motor learning: implications for physiotherapy. Physiotherapy, 93(2), 96-101.

Wulf, G., Raupach, M., & Pfeiffer, F. (2005). Self-controlled observational practice enhances learning. Research Quarterly for Exercise and Sport, 76(1), 107-111.

Wulf, G., & Toole, T. (1999). Physical assistance devices in complex motor skill learning: Benefits of a self-controlled practice schedule. Research Quarterly for Exercise and Sport, 70(3), 265-272.

Chapter 6: Self-Controlled Practice to Achieve Neuro-Cognitive Engagement: Underlying Brain Processes to Enhance Cognitive-Motor Learning and Performance

Abstract

Previous research indicates that self-controlled practice can be more effective than externally-controlled practice, which may be due, in part, to increased neurocognitive engagement. The present study seeks to investigate this possibility using electroencephalographic (EEG) measures of engagement, specifically theta power, alpha-2 power, and EEG theta coherence. Thirty-two novice participants were assigned to two groups (self-controlled and yoked) to learn the cognitive-motor skill of golf putting over the course of three days (two days of practice, and three assessments of performance). EEG measures representative of working memory engagement (theta power), central executive activity (fronto-parietal theta coherence), attention, and selective attention (alpha-2 power) were collected throughout the experiment. The self-controlled practice group was expected to show elevated neuro-cognitive engagement throughout practice, as indicated by the three EEG measures, as well as increased performance improvement on a 24hr-delayed retention test compared to the yoked group. Upon accounting for expected covariates (i.e., self-efficacy, self-confidence, goal orientations, and motivation), results from a MANCOVA applied to the EEG measures indicated that, while both groups improved the performance from baseline to retention, the self-controlled group achieved greater improvement in the number of on-target putts than the yoked group. Additionally, the EEG results revealed that the self-controlled group exhibited more consistent, and slightly greater, working memory engagement, as well as greater engagement of the

central executive, than the yoked group during practice. Interestingly, a positive relationship was observed between working memory engagement during self-controlled practice and performance improvement during performance assessment trials. These findings provide evidence of a potential mechanism by which self-controlled practice impacts learning outcomes that can be tested in future studies.

Introduction

How individuals learn cognitive-motor skills through practice has been a point of interest in science for decades. It is widely accepted that as skills become more learned, individuals move to a state of neuro-cognitive efficiency and automaticity (Fitts & Posner, 1967; Hatfield & Hillman, 2001; Rietschel et al., 2014). Fitts and Posner's classic model posits that learners begin in the cognitive stage of learning, in which performance is effortful and demanding of resources. Indeed, during the early stages of skill learning, a wide array of brain regions are activated, including the dorsolateral prefrontal cortex and various sensorimotor regions (i.e., primary, supplementary, and presupplementary motor cortices, premotor cortex, posterior parietal cortex, striatum, and the cerebellum) (Dayan & Cohen, 2011). As skill improves with practice, activity in the prefrontal and other regions non-essential to motor execution reduce, while the resultant performance becomes more facile and "automatic". This process of acquiring high levels of skill, however, takes upwards of 10 years, or 10,000 hours, for complex, "real-world" tasks (Ericsson, Krampe, & Tesch-Römer, 1993; Gobet & Campitelli, 2007; Simon & Chase, 1973; Ward, Hodges, Williams, & Starkes, 2004).

Many ideas and strategies to improve and accelerate skill learning have been developed (Ericsson, 2008; Ericsson et al., 1993; Sweller, 1988, 2010). One theoretical framework, developed by Guadagnoli and Lee (2004), is known as the challenge point framework (CPF). The CPF makes three basic assumptions: 1) too much task demand impedes learning, 2) too little task demand impedes learning, 3) there is an optimal amount of task demand which can improve and expedite learning, termed the "optimal challenge point". Guadagnoli and Lee argue that this optimal challenge point is a function of qualities of both the learner and the task itself, such that one person's optimal level of task demand will be different than another person's. As such, determination of such individual-specific practice conditions is difficult.

However, one idea has been proposed to address this issue by allowing learners to control aspects of their practice routine, aptly named "self-controlled practice". Investigations into self-controlled practice have revealed that it improves skill retention and transfer over the course of practice and, most importantly, leads to improved skill retention and transfer (Andrieux, Boutin, & Thon, 2016; Janelle, Kim, & Singer, 1995; Wulf, Raupach, & Pfeiffer, 2005). This implies that learners undergoing self-controlled practice are operating at or closer to their unique optimal challenge point than externally-controlled learners.

Various elements of practice can be self-controlled including access to feedback (Chiviacowsky & Wulf, 2002; Janelle et al., 1995), the usage of demonstration (Wulf et al., 2005) and assistive devices (Hartman, 2007; Wulf & Toole, 1999), as well as task difficulty (Andrieux et al., 2016; Andrieux, Danna, & Thon, 2012). In addition to the potential to provide individually-appropriate levels of challenge, Wulf (2007) argues that self-controlled practice increases learner motivation, which promotes a deeper level of task-relevant neurocognitive processing/engagement and has a positive impact on retention, especially at earlier "cognitive" stages of learning (Pachman, Sweller, & Kalyuga, 2013). Indeed, Grand et al. (2015) provided support for elements of Wulf's model, in that a group with self-control of access to augmented feedback reported greater intrinsic motivation and processed this feedback to a greater degree as assessed by event-related potentials from the electroencephalogram (EEG).

While the findings of Grand et al. (2015) provide some evidence that the brain is more engaged during the processing of performance feedback under self-controlled practice conditions, what is still unknown is the overarching state of the brain during a session of self-controlled practice and if it is one of increased neurocognitive engagement. Various elements of the EEG have been related to neurocognitive processes necessary to task engagement and learning, specifically memory and attention. For example, theta band activation (4 – 8 Hz), often measured from sites on the anterior region of the scalp, is representative of task-relevant working memory (WM) processes (Jensen & Tesche, 2002; Sauseng, Griesmayr, Freunberger, & Klimesch, 2010), and has been linked with attentional processes (Gevins, Smith, McEvoy, & Yu, 1997) and information encoding (Klimesch, 1999), in a positive manner (i.e., when theta power increases, WM activation increases). Additionally, high-alpha band power, also known as "alpha-2" power (11 – 13 Hz), specifically as recorded from parietal regions, is widely held to be representative of task-relevant selective attentional processes (Deeny, Hillman, Janelle, & Hatfield, 2003; Foxe & Snyder, 2011; Smith, McEvoy, & Gevins, 1999) in an inverse fashion (i.e., when alpha-2 power decreases, attention increases). This inverse relationship has been explained based on empirical findings indicative of an inhibitory phenomenon underlying alpha (Klimesch, Sauseng, & Hanslmayr, 2007; Mathewson et al., 2011). In other words, alpha-2 power is positively related to cortical inhibition. Additionally, alpha-2 power have been related to long-term memory (LTM) engagement (Klimesch, 1996, 1999; Klimesch, Doppelmayr, Pachinger, & Ripper, 1997), which may be due to the inhibition of task-irrelevant knowledge pathways and the relative enhancement of task-relevant knowledge pathways (Klimesch, 2012).

Finally, EEG theta band coherence between frontal and parietal sites is indicative of activity of the central executive component of WM (Anguera et al., 2013; Mizuhara & Yamaguchi, 2007; Payne & Kounios, 2009; Sauseng, Klimesch, Schabus, & Doppelmayr, 2005), which serves as the top-down director of attention and an interface between WM and LTM (Baddeley, 2012; Cowan, 2008), in a positive manner (i.e., when theta coherence increases, so too does central executive activity). Taken together, if self-controlled practice promotes neurocognitive engagement, greater theta power and theta coherence and reduced alpha 2 power should be observed in learners undergoing self-controlled practice relative to those undergoing externally-controlled practice.

While the learning benefits of self-controlled practice may be related to effective engagement of the brain, it is prudent to control for other factors that may affect this relationship. As mentioned by Wulf (2007), self-controlled practice improves motivation to execute the task and it may be that motivation affects learning outcomes in a separate and unique way beyond neural engagement. Furthermore, goal orientations may be a more specific method of assessing motivation during the various stages of learning and performance. It has been shown that when task demands are high, task-orientation facilitates learning (Fisher & Ford, 1998; Yeo & Neal, 2004). Alternatively, high ego-orientation may facilitate outcomes during performance stages. Additionally, a high level of self-efficacy, which is the sense of one's ability to accomplish what one sets out to do, tends to improve learning outcomes in self-controlled environments (Bandura & Schunk, 1981; Zimmerman, 2000). High levels of confidence may have a similar effect (Badami, Vaez Mousavi, Wulf, & Namazizadeh, 2012). Due to the presence of such relationships between these variables and motor skill learning, it is theoretically justified to account for and control these variables when investigating self-controlled practice.

To assess if increased neurocognitive engagement is a mechanism by which self-controlled practice provides a benefit to learning over an externally-imposed practice schedule, two groups of novice individuals (self-controlled and yoked) were asked to learn a golf putting task over the course of three days (two practice days, one performance day) while EEG activity was monitored throughout the practice and performance phases. A self-report measure of effort in the form of the "Effort" subscale of the NASA TLX (Hart & Staveland, 1988) was also used to assess subjective feelings of task effort. The employment of a yoked control group is prudent for investigations of self-controlled practice's effects on learning and performance, as individuals in the yoked group will follow identical practice schedules as those in the self-controlled group, eliminating potential confounding effects of specific practice schedules (Keetch & Lee, 2007).

During the practice period, the self-controlled group was hypothesized to exhibit greater frontal EEG theta power and EEG theta coherence between the frontal and parietal recording sites, along with lower parietal alpha-2 power, illustrative of greater working memory engagement, central executive activity, and task-related attention and long-term memory engagement, respectively, relative to the yoked group. Also, it was expected that subjective effort would be greater for the self-controlled group. The self-controlled group was also expected to exhibit improved learning outcomes (i.e., greater performance gains from the first visit to the third visit) relative to the yoked group. Finally, since three days of practice by a novice group will not result in achievement of automaticity or expertise in golf putting (Dayan & Cohen, 2011; Fitts & Posner, 1967), the self-controlled group was expected to maintain elevated levels of neurocognitive engagement during performance testing (i.e., increased EEG theta power and EEG theta coherence, and reduced parietal EEG alpha-2 power) and be characterized by higher subjective effort relative to the yoked group.

Two exploratory analyses were also conducted. First, the relationships between the EEG measures gathered during practice, indicative of neurocognitive engagement, and the learning outcome measures were assessed via correlational analyses to determine if neurocognitive engagement during practice impacts learning outcomes (i.e., performance on day three relative to day one). Finally, an exploratory analysis was conducted to determine if the relationship between self-controlled practice and learning outcomes was mediated by the EEG measures indicative of neurocognitive engagement.

Methods

Participants

Thirty-two healthy, right-handed participants from the Washington DC Metropolitan area between the ages of 18-40 years with little to no experience playing golf (≤ 5 rounds of golf/mini-golf over one's lifetime and ≤ 2 rounds golf/mini-golf during the past year) participated in this study. These 32 participants (16 females) were randomly assigned into two groups of 16 and matched for sex. Participants were compensated $50 for their time, awarded over the course of three visits (V1: $5, V2: $5, V3: $40).

Materials

The task required the use of a standard golf putter and ball and all participants used the same putter and golf ball to perform all putts. The target was a fabric circle with a diameter of 4 inches, the same size as a regulation golf hole. A putting practice hole was not used for two reasons: 1) to prevent the ball from being deflected off the side of the device in the event of a miss, which would affect the recorded distance from the hole, and 2) to discourage participants from putting too forcefully, thereby hitting the ball off the putting surface. A fabric target allowed participants to focus solely on landing their putts as close to the target as possible.

EEG activity was recorded using an electrode cap with active tin electrodes (Brain Products GmbH, Germany), which make the signal less susceptible to movement artifact, and sampled at a rate of 1000 Hz. Twenty-seven electrodes were placed on the scalp according to the international 10-20 system. The EEG record was referenced online to the left mastoid (M1) and grounded at the site AFz. An electrode was also placed on the right mastoid (M2) for re-referencing purposes. Vertical electro-oculogram (EOG) was recorded superior and inferior to the right eye. Horizontal EOG was recorded at the outer canthi of both eyes. Electrode impedances were kept below 10kΩ for the duration of the experiment.

Inertial data, indicative of the putter movement, was measured using an MTw inertial measurement unit (IMU) (XSens, The Netherlands) with a sampling rate of 100 Hz. Transistor-transistor logic (TTL) trigger pulses were sent from the IMU to the EEG for synchronization of the two signals at the start and the stop of IMU recording.

The NASA-Task Load Index (TLX) (Hart & Staveland, 1988) was used to assess self-reported perceptions of task load across six dimensions (mental demand, physical demand, temporal demand, performance, effort, and frustration) as a manipulation check. All six dimensions were scored on a 0-100 point scale in increments of 5 with 0 representing low levels of the dimension (e.g., low mental demand) and 100 representing high levels of the dimension (e.g., high mental demand). Participants placed a mark on each scale to rate feelings of intensity regarding each construct.

A self-efficacy inventory, measuring both self-efficacy magnitude and strength, and similar to that described by Myers and Feltz (2007) was used to measure task-specific self-efficacy for use as a statistical control (i.e., covariate). The inventory consists of the same statement presented at varying degrees of difficulty in series (“I have the skills and resources to successfully putt the ball from [1-10] feet”).

Participants responded with a “yes” or a “no” to each question. For every “yes” response, participants were asked to rate the level of confidence in their ability to succeed at that level from 1 to 100%. A total self-efficacy score was then calculated by summing these scores across all statements with a range of possible scores from 0 to 1000.

The Task and Ego Orientation in Sport Questionnaire (TEOSQ) (Duda, 1989) was also used to assess the extent of task- and ego-orientations for use as statistical controls (i.e., covariates). The questionnaire consisted of thirteen “I feel most successful in sport when…" statements (i.e., I am the only one who can do the play or the skill; I learn a new skill and it makes me want to practice more) and employed a 5-point Likert-type scale to capture the response. Six of these statements reflect an ego-orientation and seven reflect a task-orientation. The responses to the individual statements within each orientation type were summed to create scores for task-orientation and ego-orientation.

Separate visual analog scales (VAS) to assess confidence, motivation, and interest were used to measure the respective constructs using a horizontal line measuring 100 mm in length for use as statistical controls (i.e., covariates). The left portion of the line reflects low levels of the construct (e.g., low confidence) while the right portion of the line reflects high levels of the construct (e.g., high confidence). Participants were asked to place a vertical line at a point along the horizontal to indicate the level of their subjective experience. The distance from the left-most end of the horizontal line to the vertical marked by the participant was measured in mm to assess the self-reported intensity of each construct.

Procedure

This was a multiple visit experiment consisting of three visits (V1, V2, and V3) over the course of three consecutive days. There was a total of three performance assessments in this experiment, conducted at the beginning of each of the three visits, which each consisted of ten golf putts from a distance of 5 ft away from the target. During V1 and V2, the performance assessment was followed by two practice blocks (each consisting of 40 putts at distances up to a maximum of 10 ft) and a post-test, which consisted of ten putts from a distance of 5 ft away from the target. EEG was recorded during all performance assessments and practice blocks. Regarding self-report measures, at the beginning of each visit, participants completed a TEOSQ to assess the extent to which they were task- or ego-oriented. Before each block, participants completed a self-efficacy questionnaire, and a VAS assessing participant confidence in task performance. After each block, participants completed a TLX questionnaire to assess subjective task load and a VAS assessing level of participant motivation. See Figure 11 for a graphical representation of the procedure.

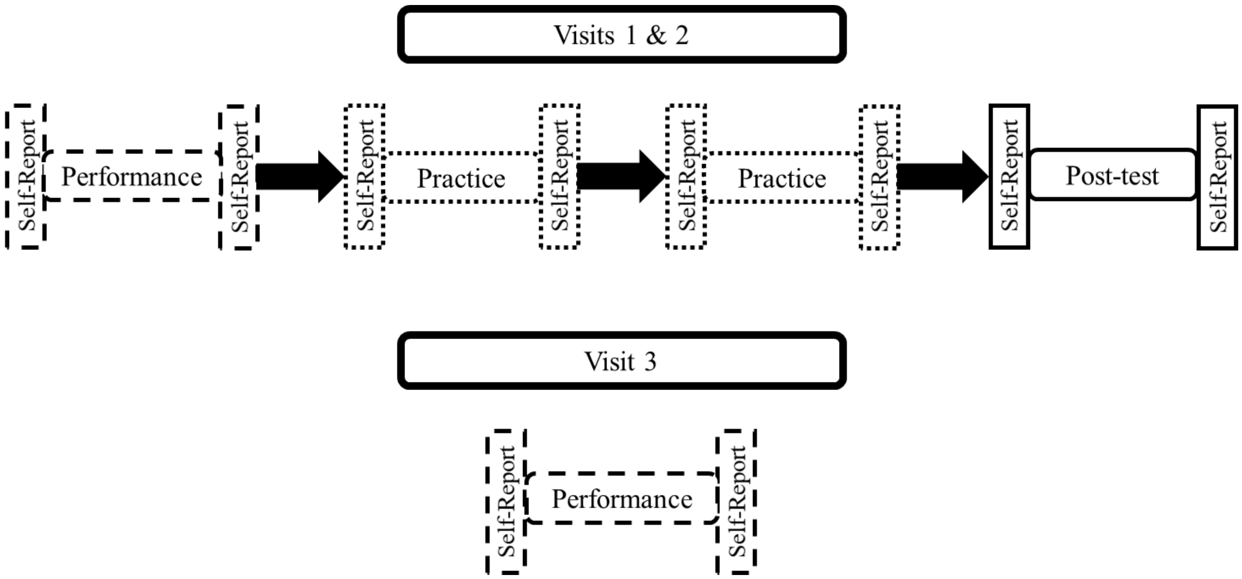

Figure 11. Performance blocks each consisted of ten putts at a distance of 5 ft. Practice blocks each consisted of 40 putts at varying distances based upon the selections of participants in the self-controlled group. “Self-Report” refers to the subjective measures of task demand (NASA-TLX), self-efficacy, goal orientations (TEOSQ), confidence (VAS), motivation (VAS), and interest (VAS). Analysis of practice trials utilized information from trials during the “Practice” blocks (dotted outline). Analysis of performance trials utilized information from trials during “Performance” blocks (dashed outline). Data from post-test blocks (which consisted of ten putts at a distance of 5 ft) were not utilized to test the present hypotheses.

Once a participant arrived on V1, s/he was provided a general description of the task alongside an informed consent. Once the participant agreed to participate and signed the consent form, s/he was given a brief verbal explanation concerning the general format of the experiment (Appendix A.). Upon confirmation of understanding of this information, the participant was assigned to an experimental group based upon their participant number, given the Edinburgh Handedness Inventory to verify that s/he was indeed right-handed, and had his/her head measured to ensure proper EEG cap fitment. The EEG cap was subsequently fitted to the participant.

Before the first putt, the participant was given verbal instructions concerning the Performance block (Appendix A.). Upon confirmation of comprehension, the participant completed a performance assessment, during which EEG data were collected. Putting performance (i.e., distance from the target in cm) was logged upon the completion of each putt. If the ball stopped while in contact with the target, it was marked as a distance of 0 cm or a "hit". Putter dynamics were logged using the IMU to synchronize the EEG signal with critical instances of task performance (i.e., the point of putter and ball contact). Once the performance assessment was completed, participants were informed that the practice blocks would commence, and given appropriate instructions depending on experimental group (Appendix A.).

Participants in the self-controlled group had complete control over the putting distance and were free to adjust distance after the completion of every putt. Participants in the yoked group followed the sequence of a previously completed self-controlled group participant and were not able to independently or autonomously change task difficulty. During the practice blocks, all participants were asked to concentrate their efforts on learning how to successfully putt the ball and that upon the completion of the experiment, they would be asked to putt the ball 10 times from a "set distance" (5 ft, which was at this point unbeknownst to the participant) within the pre-specified practice range (from 1 ft to 10 ft) to the best of their ability as a test of how much they have learned. As an added incentive, the participant with the highest number of successful putts among all participants within his/her group during the retention test received a bonus reward of $50.

When ready, participants were told that the first block of practice would then commence with EEG recording. Putting distance and performance were logged for each putt. Upon completion of the block, the participant was given a short break, if desired. Once ready, the second and final block of practice for that visit commenced. Upon the completion of the final block of practice, the participant was again offered a short break. Once ready, the post-test (ten putts at a distance of 5 ft) was performed, and, when completed, were excused for the day. The same routine was followed for both V1 and V2.

During the third and final visit (V3), participants performed a final performance assessment (ten putts from a distance of 5 ft) to evaluate learning via changes in performance between visits, specifically V1 and V3. Upon the completion of this performance assessment, participants were provided with a VAS questionnaire assessing participant interest in the study. The participants were thereafter debriefed about the nature of the experiment and excused from the study.

Data Processing

All EEG data processing was conducted using Brain Products Analyzer 2 software (Brain Products GmbH, Germany). First, the data were visually inspected for excessive noise and muscle activity. Data were subsequently re-referenced to an averaged ear montage and bandpass filtered using an IIR filter (0.01 - 50 Hz). An independent components analysis (ICA) designed to reduce ocular artifacts (blinks and eye movements) in the EEG signal was then conducted using a relative variance calculation based upon signals from both vertical and horizontal electrooculograms collected concurrently in the EEG data (Li, Ma, Lu, & Li, 2006; Plank, 2013). The 4-s period of EEG recording before putter-ball contact for each trial was extracted from the data based upon event-markers derived from the IMU data and were further segmented into four 1-s epochs, that were subsequently mean baseline corrected. Data segments were then inspected one final time to verify quality and were subsequently converted into the spectral domain using a Fast Fourier transform (FFT). Each transformed epoch of each trial within a block was then averaged with matching epochs to generate four averaged spectral epochs for that block and exported into Matlab, integrated into functional bands of interest based around the individual alpha frequency (IAF) to account for individual differences (Doppelmayr, Klimesch, Pachinger, & Ripper, 1998), and converted to decibels for statistical testing. Functional bands of interest based upon the IAF are defined as follows: Theta (6Hz-IAF – 4Hz-IAF), Alpha 2 (IAF – IAF+2Hz). Coherence was calculated as magnitude squared coherence using the "mscohere" function in Matlab between the frontal midline (Fz) and the five regions of the brain (frontal (F3 and F4), temporal (T3 and T4), central (C3 and C4), parietal (P3 and P4), and occipital (O1 and O2)) as described in other studies (Deeny, Haufler, Saffer, & Hatfield, 2009; Deeny et al., 2003).

Task performance was measured in terms of 1) the number of "hits" and 2) the distance from the target, or "error". Error was quantified in two distinct ways: radial error (RE; linear distance from the target) and variable error (VE; standard deviation of the radial error) based upon prior work by Andrieux et al. (2012).

Statistical Design

Practice Trials.

Only data from practice trials were examined in the following analyses.

To test for differences in the EEG time series recorded during practice between groups, the two EEG spectral measures of interest (i.e., theta power and alpha-2 power) and EEG theta coherence were subjected to a 2 x 2 x 2 x 2 x 5 x 4 mixed-effect repeated measures MANCOVA comprised of the following independent variables: Group (Self-Controlled and Yoked) x Visits (V1 and V2) x Block (Block 1 and Block 2) x Hemisphere (Left and Right) x Regions (Frontal, Temporal, Central, Parietal, and Occipital) x Seconds (4 s, 3 s, 2 s, and 1 s prior to putter-ball contact). A multivariate approach was considered optimal to investigate the current EEG data as the various measures of interest were simultaneously derived from the common neural EEG time series in an effort to understand the overarching neurocognitive state of the participants, while also affording the option to observe each individual metric independently. Significant effects from the MANCOVA were further investigated using univariate ANCOVAs.

To test for differences in subjective effort during practice between groups, effort scores were subjected to a 2 x 2 x 2 mixed-effect repeated-measures ANCOVA consisting of the following independent variables: Group (Self-Controlled and Yoked) x Visit (V1 and V2) x Block (Block 1 and Block 2). For all MANCOVAs and ANCOVAs, the following covariates were utilized: motivation, task- and ego-orientation, self-efficacy, and confidence. Furthermore, Fisher's Least Squared

Difference (LSD) post-hoc pairwise comparisons, with a Benjamini-Hochberg correction (false discovery rate = 0.1) to reduce type I error, were employed to further evaluate main effects and interactions of interest.

Performance Trials.

Only data from performance assessment trials were examined in the following analyses.

To test for changes in performance over the experiment between groups, the three performance metrics (i.e., radial error, variable error, and hits) were subjected to a 2 x 3 mixed effects repeated-measures MANCOVA consisting of the following independent variables: Group (Self-Controlled and Yoked) x Visit (V1, V2, and V3). Significant effects from the MANCOVA were further investigated using univariate ANCOVAs.

To test for differences in the EEG time series recorded over performance trials between groups, the three EEG spectral measures of interest were subjected to a 2 x 3 x 2 x 5 x 4 mixed effect repeated-measures MANCOVA consisting of the following independent variables: Group (Self-Controlled and Yoked) x Visit (V1, V2, and V3) x Hemisphere (Left and Right) x Regions (Frontal, Temporal, Central, Parietal, and Occipital) x Seconds (4 s, 3 s, 2 s, and 1 s prior to putter-ball contact). Again, significant effects from the MANCOVA were further investigated using univariate ANCOVAs.

Also, to test for changes in subjective effort over performance trials between groups, effort scores were subjected to a 2 x 3 mixed effect repeated-measures ANCOVA consisting of the following independent variables: Group (Self-Controlled and Yoked) x Visit (V1, V2, and V3). For all MANCOVAs and ANCOVAs, the following covariates were utilized: motivation, task- and ego-orientation, self-efficacy, and confidence. Furthermore, Fisher's Least Squared Difference (LSD) post-hoc pairwise comparisons, with a Benjamini-Hochberg correction (false discovery rate = 0.1) to reduce type I error, were employed to further evaluate main effects and interactions of interest.

Correlational Analyses.

Bivariate correlations were conducted between the three EEG metrics (averaged across practice trials) and performance improvement across performance assessments (V1 to V3) to test for relationships between measures of neurocognitive engagement during practice and learning outcomes. A Benjamini-Hochberg correction with a false discovery rate of 0.1 was used to reduce type I error.

Mediational Analyses.

Finally, to test whether EEG indicators of neurocognitive engagement mediate the relationship between self-controlled practice and learning outcomes, three path analyses were performed using the SPSS plug-in PROCESS (Hayes, 2013) using Group as the predictor variable, Performance Improvement (Hits, Radial Error, and Variable Error; V1 minus V3) as the criterion, and average EEG theta power, alpha-2 power, and theta coherence across all practice trials were examined as mediators.

Results

Brain Dynamics and Subjective Effort During Practice Trials

Brain dynamics - EEG

A mixed factorial MANCOVA comprised of between-subjects (Group) and repeated measures (Visit, Block, Hemisphere, Region, and Second) variables revealed a multivariate Group x Region x Second interaction (Hotelling's Trace: 0.176, F(36,998) = 1.624, p = 0.012, $\eta p^2 = 0.055$) significant at the level of 0.05. Further inspection using univariate ANCOVAs revealed a significant interaction effect for EEG theta power (F(12, 336) = 2.373, p = 0.006, $\eta p^2 = 0.078$). Further post-hoc inspection revealed that EEG theta power remained relatively unchanged in the temporal regions of the self-controlled group as the time to ball contact was approached ((t-3Sec) vs (t-2Sec): p = 0.028, d = 0.409), while it was progressively reduced in this brain region in the yoked group (F(3,84) = 4.809, p = 0.004, $\eta p^2 =$ 0.147; (t-4Sec) vs (t-3Sec): p = 0.044, d = 0.373; (t-4Sec) vs (t-2Sec): p = 0.004, d = 0.549; (t-4Sec) vs (t-1Sec): p < 0.001, d = 0.993; (t-3Sec) vs (t-1Sec): p = 0.006, d = 0.529; (t-2Sec) vs (t-1Sec): p = 0.011, d = 0.481) across both practice days (i.e., Visit 1 and 2). See Figure 12.

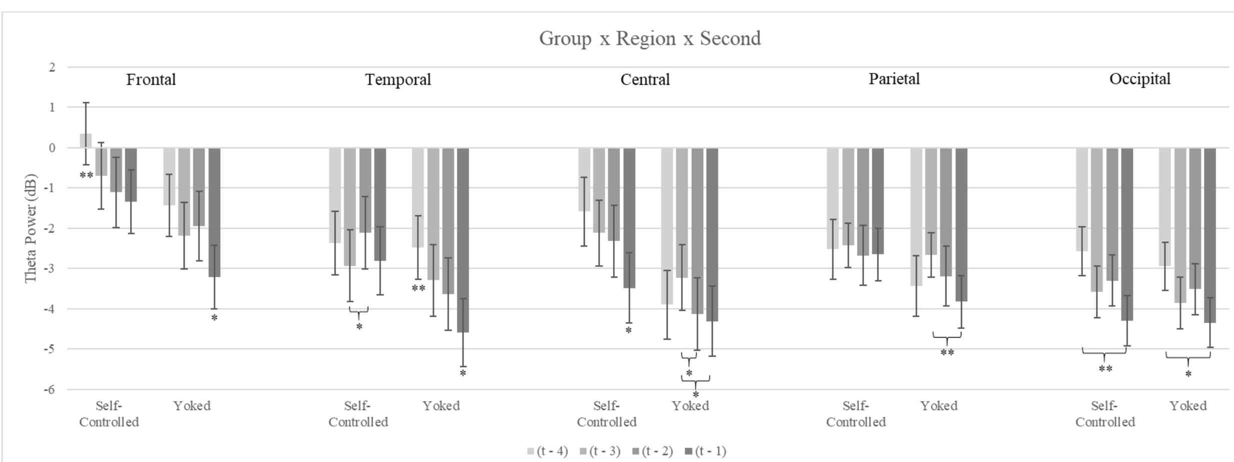

Figure 12. Group x Region x Second interaction for EEG theta power. (t – 4), (t – 3),

(t – 2), and (t – 1) refers to 4, 3, 2, and 1 seconds prior to putter-ball contact, respectively. * : $p < 0.05$; ** : $p < 0.01$.

In addition, the MANCOVA revealed an interaction of Group x Hemisphere x Visit (Hotelling's Trace: 0.271, $F(3,26) = 2.345$, $p = 0.096$, $\eta p^2 = 0.213$) significant at the level of 0.1. Further inspection using univariate ANCOVAs revealed a significant interaction effect for EEG theta coherence $F(1,28) = 6.765$, $p = 0.015$, $\eta p^2 = 0.195$). Consistent with the conceptual model of greater neurocognitive engagement with self-controlled practice, EEG theta coherence observed in the left hemisphere of the self-controlled group was higher relative to that observed in the corresponding (i.e., left) hemisphere in the yoked group during V1 ($p = 0.008$, $d = 0.505$), and was further defined by an asymmetry of hemispheric cortico-cortical communication in the self-controlled group, such that coherence was elevated in the left hemisphere relative to the right, on both days of practice (V1: $p < 0.001$, $d = 0.801$; V2: $p = 0.045$, $d = 0.364$) while no such asymmetry was observed in the control group. Finally, a significant reduction in left hemispheric theta coherence was observed from V1 to V2 in the self-controlled group ($p = 0.009$, $d = 0.491$) while no such difference was observed in the yoked group (See Figure 13).

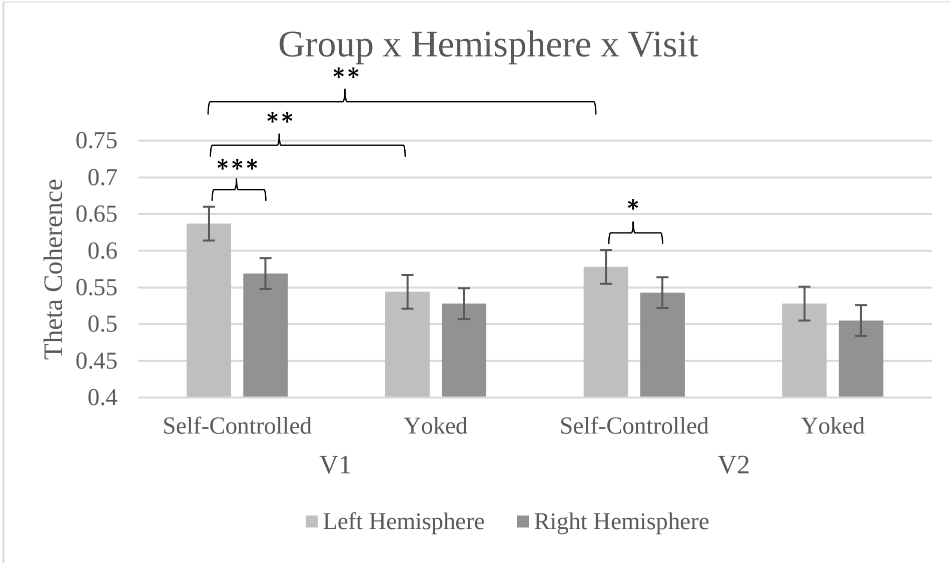

Figure 13. Group x Hemisphere x Visit interaction for EEG theta coherence. V1: Visit 1; V2: Visit 2. * : p <0.05; ** : p < 0.01; *** : p < 0.001.

An interaction between Group x Region, significant at the level of 0.1, was also revealed by the MANCOVA (Hotelling's Trace: 0.175, $F(12,326) = 1.584$, $p = 0.095$, $\eta p^2 = 0.055$). Further investigation using univariate ANCOVAs revealed a significant interaction effect for EEG theta coherence ($F(4,112) = 2.162$, $p = 0.101$, $\eta p^2 = 0.073$). While the univariate interaction did not reach significance at the 0.1 level, pairwise comparisons of the means were conducted in light of the a priori expectations of regional effects in theta coherence, in that group differences were expected for fronto-parietal theta coherence, specifically. As expected, significant group differences were observed within the parietal region ($p = 0.016$, $d = 0.449$), as well as in the occipital region ($p = 0.034$, $d = 0.401$), while marginal differences were also observed in temporal regions ($p = 0.064$, $d = 0.331$), such that the self-controlled group displayed greater theta coherence than the yoked group in those regions[1]. See Figure 14.

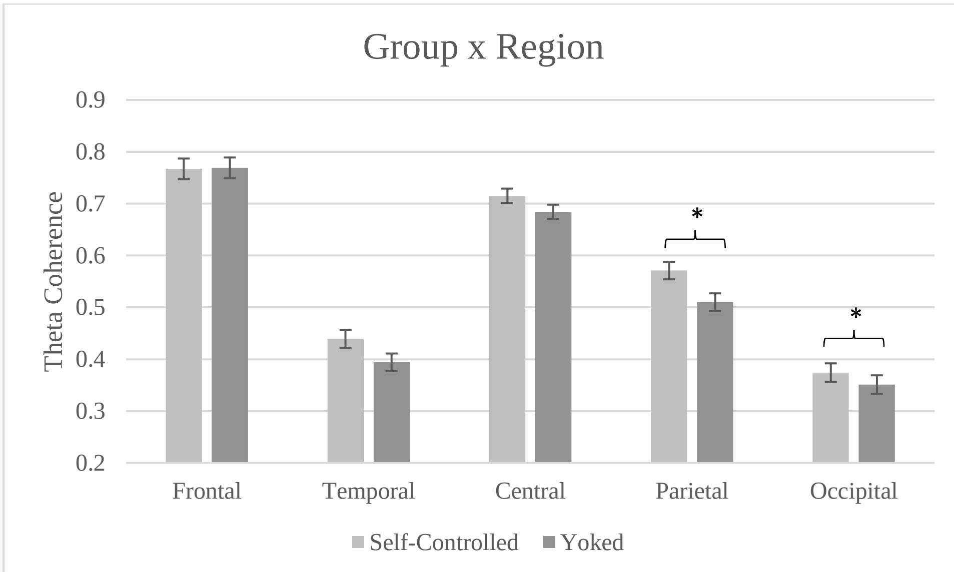

Figure 14. Group x Region interaction for EEG theta coherence. * : $p < 0.05$.

Finally, a significant Group x Region x Visit interaction was detected for EEG theta power ($F(4,112) = 2.522$, $p = 0.045$, $\eta p^2 = 0.083$) at the 0.05 level, such that the self-controlled group displayed greater frontal bias in theta power (Frontal vs Temporal: $p < 0.001$, $d = 0.767$; Frontal vs Central: $p < 0.001$, $d = 0.997$; Frontal vs Parietal: $p < 0.001$, $d = 0.803$; Frontal vs Occipital: $p < 0.001$; $d = 1.188$) than the yoked group (Frontal vs Temporal: $p = 0.004$, $d = 0.559$; Frontal vs Central: p

[1] Indeed, conducting an ANCOVA for theta coherence using the theoretically-predicted parietal and temporal regions (Başar, Schürmann, & Sakowitz, 2001) yielded a significant effect for group ($F(1,28) = 6.277$, $p = 0.018$, $\eta p^2 = 0.183$) compared to the smaller effect for group revealed from an ANCOVA using all five regions ($F(1,28) = 4.318$, $p = 0.047$, $\eta p^2 = 0.134$).

<0.001, d = 0.763; Frontal vs Parietal: p = 0.002, d = 0.597; Frontal vs Occipital: p = 0.020, d = 0.435), while also displaying non-significant trends such that the self-controlled group displayed greater frontal theta power than the yoked group, especially during V1 (p = 0.160, d = 0.255). See Figure 15.

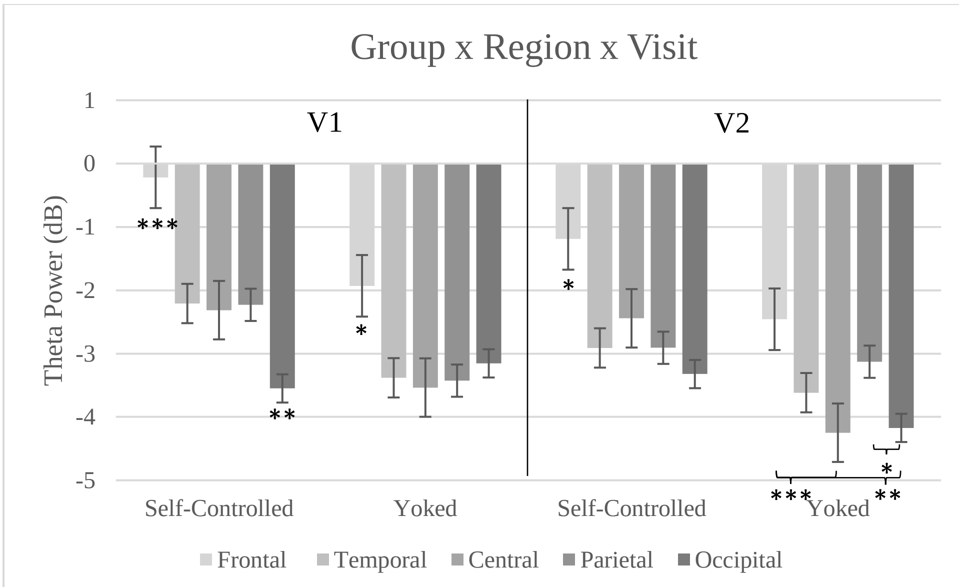

Figure 15. Group x Region x Visit interaction for EEG theta power. V1: Visit 1; V2: Visit 2. * : p < 0.05; ** : p < 0.01; *** : p < 0.001.

Subjective effort

A repeated-measures ANCOVA revealed an effect of Block (F(1,25) = 3.458, p = 0.075, $\eta p^2 = 0.122$) significant at the 0.1 level, such that effort was rated higher during the first block than during the second block by both groups. No other effects of interest were observed.

Task Performance During Performance Assessment Trials

To display evidence of skill acquisition over the course of this experiment, participants must exhibit change across visits. Indeed, a repeated measures MANCOVA applied to hits, radial error, and variable error revealed an effect for visit (Hotelling's Trace: 1.367, $F(6,94) = 10.704$, $p < 0.001$, $\eta p^2 = 0.406$), such that performance improved for both groups across V1, V2, and V3 (i.e., reductions in radial error ($F(2,50) = 31.511$, $p < 0.001$, $\eta p^2 = 0.558$), reductions in variable error ($F(2.50) = 25.569$, $p < 0.001$, $\eta p^2 = 0.506$), and increases in hit rate ($F(2,50) = 2.894$, $p = 0.065$, $\eta p^2 = 0.104$)).

While no Group x Visit interaction effect was observed for the learning outcome measure of Hits, the effect suffered from a lack of statistical power ($1 - \beta = 0.16$). Due to a priori expectations of group differences in performance improvement between the first and third visit, which would provide evidence of group differences in learning, specific contrasts were conducted between V1 and V3 for both groups using the Fisher's LSD with a Benjamini-Hochberg correction. Simple pairwise t-tests were not appropriate to perform as covariates cannot be accounted for by such as approach. Notably, it was revealed that the self-controlled group displayed significant improvement in hit rate from V1 to V3 at the 0.05 level ($p = 0.029$, $d = 0.409$), while no such improvement was observed in the yoked group. See Figure 16.

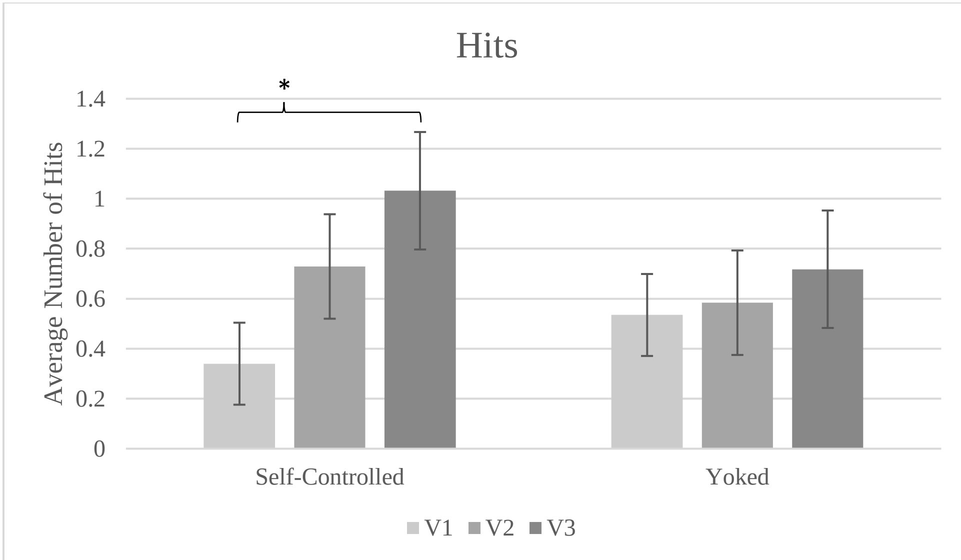

Figure 16. Group x Visit effects for Hits (average out of 10 trials) during performance trials. V1: Visit 1; V2: Visit 2; V3: Visit 3. * : $p < 0.05$.

Additionally, both radial error and variable error revealed Group x Visit interactions (radial error: $F(2,50) = 2.673$, $p = 0.085$, $\eta p^2 = 0.097$; variable error: $F(2,50) = 2.949$, $p = 0.078$, $\eta p^2 = 0.106$) significant at the 0.1 level, such that the yoked group displayed greater reductions in error than the self-controlled group across visits (radial error, yoked: V1 vs V2: $p < 0.001$, $d = 1.040$; V1 vs V3: $p < 0.001$, $d = 1.013$; radial error, self-controlled: V1 vs V2: $p = 0.007$, $d = 0.518$; V1 vs V3: $p < 0.001$, $d = 0.731$; V2 vs V3: $p = 0.041$, $d = 0.381$; variable error, yoked: V1 vs V2: $p < 0.001$, $d = 0.898$; V1 vs V3: $p < 0.001$, $d = 0.878$; variable error, self-controlled: V1 vs V2: $p = 0.036$, $d = 0.391$; V1 vs V3: $p = 0.013$, $d = 0.472$). See Figures 17 and 18.

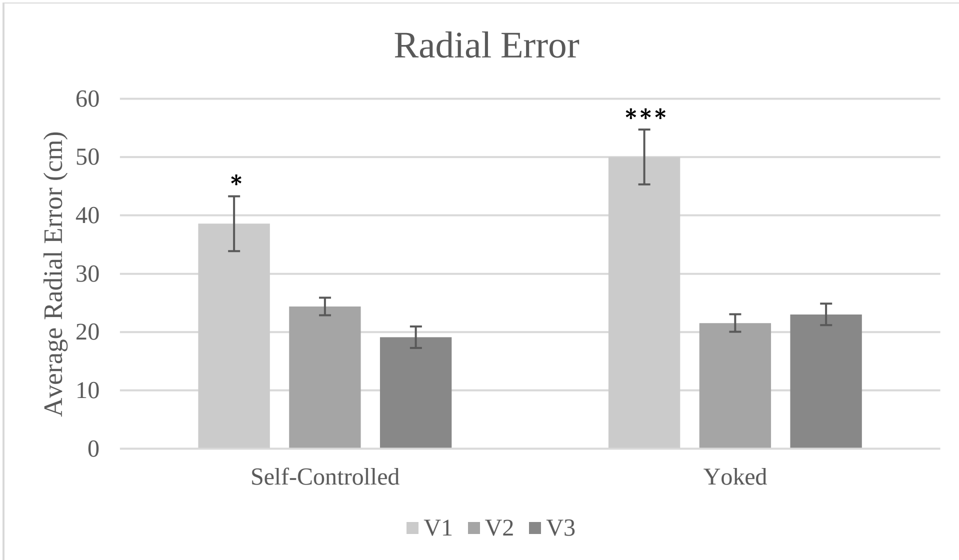

Figure 17. Group x Visit effects for Radial Error (cm) during performance trials. V1: Visit 1; V2: Visit 2; V3: Visit 3. * : $p < 0.05$; *** : $p < 0.001$.

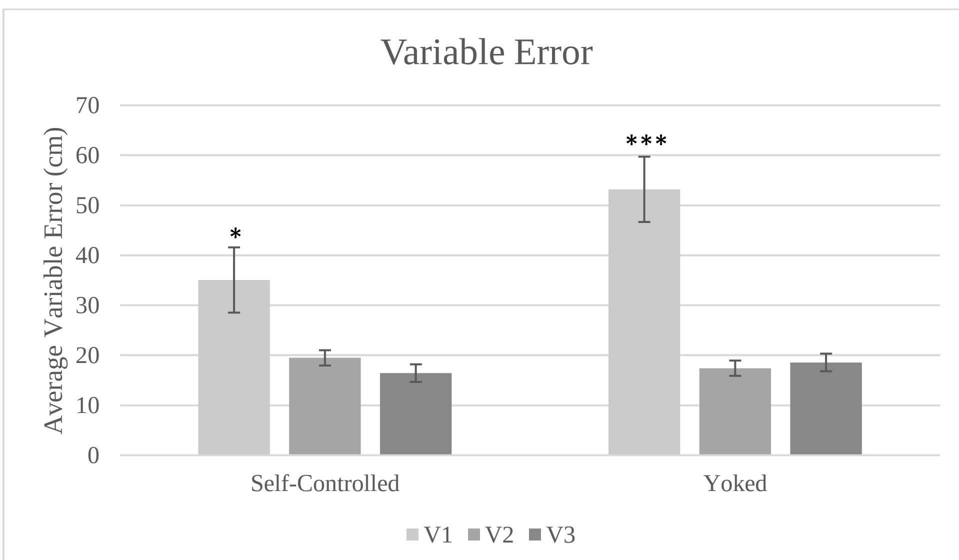

Figure 18. Group x Visit effects for Variable Error (cm) during performance trials. V1: Visit 1; V2: Visit 2; V3: Visit 3. * : $p < 0.05$; *** : $p < 0.001$.

Relationship between brain dynamics during practice trials and change in *behavioral performance during performance assessment trials*

The self-controlled group displayed a positive correlation between average frontal midline theta power during practice and hit rate improvement ($r = 0.464$, $p = 0.035$), significant and the level of 0.05, such that higher levels of theta during practice was related to greater improvement in hit rate from V1 to V3. In the yoked group, positive relationships were observed between fronto-parietal theta coherence and learning outcomes. Specifically, theta coherence between the frontal and parietal midlines during practice displayed a positive correlation with hit rate improvement during performance trials ($r = 0.507$, $p = 0.023$), significant at the 0.05 level, such that greater coherence during practice was related to greater improvements in hit rate from V1 to V3. Furthermore, coherence between frontal midline and the left parietal region displayed a positive correlation with radial error reductions during performance trials ($r = 0.510$, $p = 0.022$), significant at the 0.05 level, such that greater coherence during practice was related to greater reductions in radial error from V1 to V3.

However, upon correcting for multiple comparisons, no correlations maintained statistical significance.

Do brain dynamics during practice trials mediate the relationship between self-controlled practice and change in performance assessment trials?

The path analysis model used to investigate whether EEG measures of engagement during practice trials mediated the effect of Group on learning outcomes measures, accounting for all covariates used in the previous MANCOVA analyses, did not reveal any effects of interest for any of the three learning outcome measures.

Brain Dynamics and Subjective Effort During Performance Assessment Trials

Brain dynamics - EEG

A repeated measures MANCOVA revealed a significant Group x Second interaction (Hotelling's Trace: 0.250, $F(9,215) = 1.992$, $p = 0.042$, $\eta p^2 = 0.077$) which was driven by EEG theta power ($F(3,75) = 5.031$, $p = 0.004$, $\eta p^2 = 0.168$), such that the self-controlled group displayed reductions in theta power from three seconds prior to the putt ((t-3s) vs (t-2s): $p = 0.019$, $d = 0.444$; (t-3s) vs (t-1s): $p = 0.010$, $d = 0.490$), while the yoked group displayed significant reductions in theta power from four seconds prior to the putt ((t-4s) vs (t-3s): $p = 0.014$, $d = 0.465$; (t-4s) vs (t-2s): $p = 0.001$, $d = 0.673$; (t-4s) vs (t-1s): $p = 0.011$, $d = 0.484$; (t-3s) vs (t-2s): $p = 0.028$, $d = 0.412$). See Figure 19.

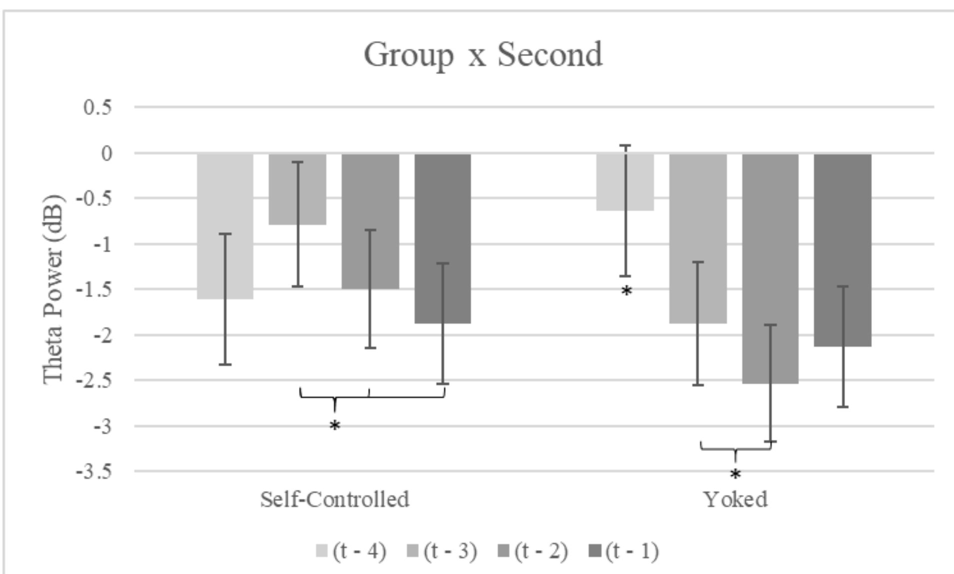

Figure 19. Group x Second effects for EEG theta power during performance trials. (t – 4), (t – 3), (t – 2), and (t – 1) refers to 4, 3, 2, and 1 seconds prior to putter-ball contact, respectively. * : $p < 0.05$.

However, to display evidence of change in cortical dynamics across performance assessments due to practice over the course of this experiment, effects for Visit must be observed. Since no effects for Visit were observed during performance assessment trials, the interactions observed are unlikely to be due to the experimental manipulation.

Subjective effort

A repeated measures ANCOVA did not reveal any main effects or interactions of interest.

Discussion

The purpose of this study was to investigate possible mechanisms by which self-controlled practice is effective from a cognitive neuroscience perspective. Using EEG, we assessed levels of neurocognitive engagement, including selective attentional processes and working memory engagement, to examine whether those engaged in self-controlled practice exhibited elevated neural activation and cortico-cortical communication during practice, indicative of heightened working memory and attentional processing, relative to those undergoing externally-imposed (yoked) practice. We also assessed changes in behavioral performance across the three visits to gauge the effectiveness of self-controlled practice to facilitate learning over externally-controlled practice.

Practice Trials

In agreement with the conceptual model, the self-controlled group displayed more consistent, and slightly greater, working memory activation and greater central executive activity during practice trials relative to the yoked group, both of which are indicative of elevated neurocognitive engagement during practice.

The present data indicate that the self-controlled group displayed relatively consistent levels of theta power in the temporal regions of the cerebral cortex in the seconds prior to the putt during practice while the yoked group displayed a progressive reduction in power as the putt approached. Interestingly, this pattern appears reversed between the groups in the central regions (i.e., the self-controlled group displayed a progressive reduction in theta activity as putt initiation approached while the yoked group exhibited no significant change). A review by Kirk and Mackay (2003) reported that temporal theta is an indicator of hippocampal theta oscillations, which has been implicated in a range of memory-related processes from encoding to retrieval, while theta oscillations in central regions are related to motor activity (Niedermeyer, Naidu, & Plate, 1997). The self-controlled group's consistent engagement of temporal theta power in the seconds preceding the putt may be indicative of mnemonic processes related to task performance (i.e., retrieval of prior motor executions, the explicit modification of previous motor plans, and the encoding of motor dynamics) to inform possible changes to their practice regimen and future motor plans, processes which may be less present in the yoked group. Indeed, there is a documented relationship between theta power and action-monitoring (Cavanagh, Cohen, & Allen, 2009; Cavanagh, Zambrano-Vazquez, & Allen, 2012; Luu, Tucker, & Makeig, 2004). Such an explanation is consistent with the notion that the self-controlled group is more actively engaged in, and utilizing more information from, practice than the yoked group. In contrast, the self-controlled group's progressive reduction in theta activity in the central regions could be interpreted as refinement of any non-essential or excessive neural activity in the motor cortex (Niedermeyer et al., 1997). Such speculation is based on the primary role of the central region in motor execution. In other words, the observed pattern of theta power in the temporal regions of the self-controlled group suggests intense mnemonic processing of task-relevant cues while the pattern of theta power observed in the central region is indicative of a refinement of neural activity related to motor behavior (Hatfield, Haufler, Hung, & Spalding, 2004).

Beyond the assessment of regional cortical activity through examination of EEG theta power, the self-controlled group also exhibited higher levels of fronto-parietal theta coherence than the yoked group throughout practice, as expected, indicative of elevated central executive activity. Indeed, as Sauseng and colleagues have shown (Sauseng et al., 2010; Sauseng et al., 2005), fronto-parietal theta coherence, or connectivity, is related to top-down control processes, especially under conditions of performing novel motor behaviors (Sauseng et al., 2007), as participants did in the present study. The central executive is responsible for attentional control in Baddeley's (2012) working memory model; Cowan (2008) also uses the concept of the central executive as the mechanism which directs attention to elements of information held in short-term memory for further processing by the working memory. Clearly, based upon these theoretical frameworks, activity of the central executive is critical to effective information processing, learning, and retrieval. Given that the self-controlled group appears to be processing greater amounts of information in working memory than the yoked group, based upon the theta power results, it seems reasonable that the central executive would exhibit increased top-down activity to direct attention amongst the various pieces of held information, as indicated by EEG theta coherence. Moreover, these findings appear to be most evident in the left hemisphere during the first visit. The specificity of this effect in the left hemisphere implies that these group differences are due to greater usage of explicit attentional control strategies by the self-controlled group given the left hemisphere's involvement in explicit, semantic processing (Binder et al., 1997; Springer & Deutsch, 1998; Vigneau et al., 2006).

There was no indication of group differences based on the results for the analysis of the EEG alpha-2 power. Klimesch and colleagues (Klimesch, 2012; Klimesch et al., 2007) provided strong evidence that alpha-2 power is inversely related to cortical activation and attention due to inhibitory processes, and the lack of a group difference implies that both groups similarly employed the attentional resources indexed by this frequency band during practice. Given that both groups were actively trying to learn the task, albeit using different practice methodologies, it is reasonable that both would be engaging comparable levels of attention during practice, despite the observed group differences in explicit executive control as indexed by EEG theta coherence. Indeed, Wulf's (2007) model made no explicit reference that self-controlled practice would directly impact task-related attentional demand. This result provides evidence to the specificity of the impact self-controlled practice has on cognitive processes, which appears to be isolated to processes related to working memory load as indicated by EEG theta power and fronto-parietal theta coherence (Sauseng et al., 2010; Sauseng et al., 2007; Sauseng et al., 2005).

Finally, participants reported that effort decreased within each of the two practice sessions, perhaps due to a combination of adaptation and fatigue. The lack of group differences in perceived effort may be due to limitations of self-report measures. Limitations of self-report measures have been documented (Podsakoff & Organ, 1986) and perceived effort can be impacted by numerous factors unrelated to the task at hand. Indeed, being novices with no other frame of reference, individuals in either group may rate their effort at similar levels.

In sum, during practice, the self-controlled group exhibited consistent and slightly greater levels of working memory load and greater central executive activity relative to the yoked group. As highlighted by various theoretical perspectives (Ericsson, 2008; Sweller, 2010; Wulf, 2007) and empirical studies (Carini, Kuh, & Klein, 2006; Janosz, 2012; Rowe, Shores, Mott, & Lester, 2010; Silverman, 1985), engagement is positively related to effective learning. These results provide the first evidence that, when controlling for factors related to confidence and motivation, self-controlled practice promotes neuro-cognitive working memory engagement during cognitive-motor learning.

Performance Improvement Across Performance Assessment Trials

Results for the number of putts landed on the target (“hits”) supported our hypotheses regarding performance improvement in that the self-controlled group exhibited a marked improvement in hits from the first to the third visit, whereas the yoked group showed little to no improvement. It is worth noting that prior to the addition of the covariates (i.e., goal orientations, motivation, self-efficacy, and confidence), both the self-controlled group and the yoked group displayed similar improvement in hits over time. This means that the increase in the number of hits exhibited by the yoked group was accounted for by the covariates, while the self-controlled group retained a significant amount of performance improvement from practice. This finding implies that the improvement in hits exhibited by the self-controlled group is driven by factors above and beyond the covariates and that other mechanisms are at play, such as working memory engagement. This result is supportive of the current EEG findings from the practice trials which indicate that the self-controlled group exhibited greater neurocognitive engagement during practice, which may relate to these improved learning outcomes.

Additionally, while both groups showed similar overall reductions in error (i.e., radial and variable) over the course of the experiment, the time course of that improvement was not the same across groups. Both radial and variable error exhibited a linear decrease in both measures in the self-controlled group relative to the yoked group, which exhibited an initial large reduction in error from first visit to the second visit followed by no change. It is possible that the underlying mechanisms by which self-controlled practice impacts learning allowed for a more controlled and continual reduction in error as learners reflected upon and executed their personal practice schedules. This trend may have continued further if the experiment contained additional visits, while the yoked group's improvement may have slowed from the second visit. However, more data are required to support this notion.

Relationships between performance improvement and neurocognitive engagement during practice

The concurrent findings of group differences in both neurocognitive engagement and performance improvement lead to the inevitable question of the presence of relationships between the two. The exploratory correlational analyses between EEG measures during practice and performance improvement from the first visit to the third visit revealed positive relationships between working memory engagement during practice and performance improvement for both the self-controlled group and the yoked group, indicating 1) the importance of working memory engagement to learning, regardless of practice methodology, and 2) the different ways the two groups leveraged their mental resources to learn the task. The self-controlled group's relationship between frontal theta power and hit rate improvement supports the notion that self-controlled practice is related to more engaged learners, specifically in terms of processing greater amounts of information relevant to hitting the target (Sauseng et al., 2010). The nature of self-controlled practice is to monitor various aspects of one's progress during the task to make decisions regarding practice organization, which involves handling and interacting with several pieces of information (Wulf et al., 2005). Thus, it is reasonable that those using self-controlled practice methods would show a relationship between working memory load, which would be increased with high information processing demands, and learning outcomes.

Contrarily, the yoked group displayed positive relationships between theta coherence and both hit rate improvement and reductions in radial error. These findings imply that, for the yoked group, attentional control via the central executive was crucial to learn the task, rather than handling a variety of pieces of task-relevant information as in the self-controlled group. The application of effort to perform a given task also means there is greater top-down control of attention to that task (Kahneman, 1973; Sarter, Gehring, & Kozak, 2006). Thus, given the limitations of the yoked group relative to the self-controlled group during practice, it is reasonable to observe that attentional control processes would be related to learning outcomes as opposed to maintaining and processing a relatively large array of information as in the self-controlled group. While the results of our exploratory correlations are interpretable based on understandings of self-controlled and externally-controlled practice, it is important to note that these findings did not maintain statistical significance upon correcting for multiple comparisons and demand further investigation to confirm or refute.

Exploratory mediational analyses largely expanding upon the above correlations did not reveal any evidence that EEG measures of neurocognitive engagement mediate the relationship between self-controlled practice and learning outcomes. That said, the participant requirements to run such an analysis successfully were not met in the present experiment, and thus the analysis suffered from a lack of statistical power. In order to successfully test such a complex model, data from many more participants are required, which was outside the practical scope of this experiment. Further work is necessary to investigate the mediational effects of cortical dynamics on cognitive-motor skill learning.

Neurocognitive variables underlying performance dynamics

During performance trials, we observed no clear differences in brain dynamics observed between the groups as we did during practice trials. Indeed, while the differences which were observed for EEG theta power may have been present at a detailed level, the general expectation that there would be some carry-over effects of greater neurocognitive engagement for the self-controlled group from practice to performance was not supported. Given the brief period of practice over the course of this experiment, which would prohibit significant progress towards expertise and automaticity, one may not expect the occurrence of notable group differences in neuro-cortical activation in the absence of a unique manipulation. Recall that during performance assessment trials, both groups putted the ball under identical circumstances (i.e., from a distance of 5 ft). Perhaps with a more extended practice period, the self-controlled group would display the classic signs of expertise, such as increased theta power (Baumeister, Reinecke, Liesen, & Weiss, 2008; Doppelmayr, Finkenzeller, & Sauseng, 2008), increased alpha power (Haufler, Spalding, Santa Maria, & Hatfield, 2000; Janelle et al., 2000), and reduced coherence (Deeny et al., 2009), at an earlier period than the yoked group given the findings that self-controlled practice provides a benefit to learning (Chiviacowsky & Wulf, 2002; Grand et al., 2015; Hartman, 2007; Wulf et al., 2005).

Conclusion

In sum, the self-controlled group displayed greater engagement of working memory resources during practice, as expected, and were able to achieve greater performance improvement over the course of the experiment in terms of target hits than the yoked group. The present results can be interpreted using Wulf's (2007) model of self-controlled practice and the challenge point framework (Guadagnoli & Lee, 2004). According to Wulf, self-controlled practice increases learner motivation, thereby promoting deeper task-relevant neurocognitive processing (i.e., greater neurocognitive engagement), which has a positive impact on learning. The present results support the aspects of the model dictating that self-controlled practice promotes greater neurocognitive engagement, specifically of working memory processes, by allowing learners to self-select an appropriate level of challenge (Guadagnoli & Lee, 2004), and that self-controlled practice positively impacts learning outcomes.

Limitations and Future Directions

Given that the self-controlled practice group achieved greater learning outcomes than the yoked group in terms of hits, it may be argued that self-controlled practice allows learners to practice closer to their unique optimal challenge point, as described in the challenge point framework (Guadagnoli & Lee, 2004). It is important to note that this effect was only observed upon accounting for the covariates. Given that self-controlled practice places much emphasis on the learner's willingness to apply his/herself to learn the task, the ability for a learner to utilize self-controlled practice to achieve his/her optimal challenge point seems to depend on such variables as motivation and confidence. Indeed, there is notable evidence that illustrates the effects of motivation and confidence on learning outcomes (Clément, Dörnyei, & Noels, 1994; Pintrich, 1999; Zusho, Pintrich, & Coppola, 2003). Thus, future work into both the challenge point framework and self-controlled practice should continue to take into account such variables. It is of further note that, even upon accounting for the covariates, we did not observe differences for the radial error and variable error measurements. It would be of interest to further investigate why not all performance outcome variables displayed the same pattern of improvement.

This experiment focused on novice learners learning a relatively complex ecologically-valid task over a limited period of time. As such, the present findings are only informative under this specific context. Future experiments should seek to either a) follow learners learning a similar skill over a longer period of time or b) have a simpler skill that would allow greater skill development in a similarly limited amount of time. While theoretical predictions are abound regarding the nature of skill progression (Fitts & Posner, 1967; Hatfield & Hillman, 2001; Schmidt, 1975), empirical evidence regarding the process of acquiring skills from a cognitive neuroscientific perspective is lacking, with few short-term (Jaquess et al., Under revision; Kerick, Douglass, & Hatfield, 2004; Landers, Han, Salazar, & Petruzzello, 1994) and no extended longitudinal studies having been conducted to explore the time course of automaticity acquisition. Not only will such studies provide further information on the specific benefits of self-controlled practice, they may inform the field of a possible method by which to elicit appropriately challenging levels of difficulty across a wide variety of disciplines.

Further studies may also wish to investigate more precisely how "optimal" a selected level of challenge is for the learner undergoing self-controlled practice. Many learning frameworks have attempted to describe and identify the optimal level of challenge for an individual to learn most effectively (Ericsson et al., 1993; Guadagnoli & Lee, 2004; Sweller, 1988), but have not systematically attempted to manipulate level of challenge over a period of time to assess effects on learning. Using a self-selected level of challenge as a base, it may be possible for experimenters to prescribe deviations from it over a period of time in an effort to learn more concerning the “optimal challenge point” (Guadagnoli & Lee, 2004). Ultimately, using measurements of brain activation such as EEG, functional magnetic resonance imaging (fMRI), or positron emission tomography (PET), it may be possible to further understand the state of the brain during this state of optimal challenge to identify the mechanisms by which information is most effectively consolidated and utilized.

Reference

Andrieux, M., Boutin, A., & Thon, B. (2016). Self-control of task difficulty during early practice promotes motor skill learning. Journal of Motor Behavior, 48(1), 57-65.

Andrieux, M., Danna, J., & Thon, B. (2012). Self-control of task difficulty during training enhances motor learning of a complex coincidence-anticipation task. Research Quarterly for Exercise and Sport, 83(1), 27-35.

Anguera, J. A., Boccanfuso, J., Rintoul, J. L., Al-Hashimi, O., Faraji, F., Janowich, J., . . . Johnston, E. (2013). Video game training enhances cognitive control in older adults. Nature, 501(7465), 97-101.

Badami, R., Vaez Mousavi, M., Wulf, G., & Namazizadeh, M. (2012). Feedback about more accurate versus less accurate trials: Differential effects on self-confidence and activation. Research Quarterly for Exercise and Sport, 83(2), 196-203.

Baddeley, A. (2012). Working memory: theories, models, and controversies. Annual Review of Psychology, 63, 1-29.

Bandura, A., & Schunk, D. H. (1981). Cultivating competence, self-efficacy, and intrinsic interest through proximal self-motivation. Journal of Personality and Social Psychology, 41(3), 586.

Başar, E., Schürmann, M., & Sakowitz, O. (2001). The selectively distributed theta system: functions. International Journal of Psychophysiology, 39(2), 197-212. doi: https://doi.org/10.1016/S0167-8760(00)00141-0

Baumeister, J., Reinecke, K., Liesen, H., & Weiss, M. (2008). Cortical activity of skilled performance in a complex sports related motor task. European Journal of Applied Physiology, 104(4), 625-631.

Binder, J. R., Frost, J. A., Hammeke, T. A., Cox, R. W., Rao, S. M., & Prieto, T. (1997). Human brain language areas identified by functional magnetic resonance imaging. Journal of Neuroscience, 17(1), 353-362.

Carini, R. M., Kuh, G. D., & Klein, S. P. (2006). Student engagement and student learning: Testing the linkages. Research in Higher Education, 47(1), 1-32.

Cavanagh, J. F., Cohen, M. X., & Allen, J. J. (2009). Prelude to and resolution of an error: EEG phase synchrony reveals cognitive control dynamics during action monitoring. Journal of Neuroscience, 29(1), 98-105.

Cavanagh, J. F., Zambrano-Vazquez, L., & Allen, J. J. (2012). Theta lingua franca: A common mid-frontal substrate for action monitoring processes. Psychophysiology, 49(2), 220-238.

Chiviacowsky, S., & Wulf, G. (2002). Self-controlled feedback: Does it enhance learning because performers get feedback when they need it? Research Quarterly for Exercise and Sport, 73(4), 408-415.

Clément, R., Dörnyei, Z., & Noels, K. A. (1994). Motivation, self-confidence, and group cohesion in the foreign language classroom. Language Learning, 44(3), 417-448.

Cowan, N. (2008). What are the differences between long-term, short-term, and working memory? Progress in Brain Research, 169, 323-338.

Dayan, E., & Cohen, L. G. (2011). Neuroplasticity subserving motor skill learning. Neuron, 72(3), 443-454.

Deeny, S. P., Haufler, A. J., Saffer, M., & Hatfield, B. D. (2009). Electroencephalographic coherence during visuomotor performance: a comparison of cortico-cortical communication in experts and novices. Journal of Motor Behavior, 41(2), 106-116.

Deeny, S. P., Hillman, C. H., Janelle, C. M., & Hatfield, B. D. (2003). Cortico-cortical communication and superior performance in skilled marksmen: an EEG coherence analysis. Journal of Sport and Exercise Psychology, 25(2), 188-204.

Doppelmayr, M., Finkenzeller, T., & Sauseng, P. (2008). Frontal midline theta in the pre-shot phase of rifle shooting: differences between experts and novices. Neuropsychologia, 46(5), 1463-1467.

Doppelmayr, M., Klimesch, W., Pachinger, T., & Ripper, B. (1998). Individual differences in brain dynamics: important implications for the calculation of event-related band power. Biological Cybernetics, 79(1), 49-57.

Duda, J. L. (1989). Relationship between task and ego orientation and the perceived purpose of sport among high school athletes. Journal of Sport and Exercise Psychology, 11, 318-335.

Ericsson, K. A. (2008). Deliberate practice and acquisition of expert performance: A general overview. Academic Emergency Medicine, 15(11), 988-994.

Ericsson, K. A., Krampe, R. T., & Tesch-Römer, C. (1993). The role of deliberate practice in the acquisition of sports expertise. Psychological Review, 100, 363-406.

Fisher, S. L., & Ford, J. K. (1998). Differential effects of learner effort and goal orientation on two learning outcomes. Personnel Psychology, 51(2), 397-420.

Fitts, P. M., & Posner, M. I. (1967). Human Performance. Oxford, England: Brooks/Cole.

Foxe, J. J., & Snyder, A. C. (2011). The role of alpha-band brain oscillations as a sensory suppression mechanism during selective attention. Frontiers in Psychology, 2, 154.

Gevins, A., Smith, M. E., McEvoy, L., & Yu, D. (1997). High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. Cerebral Cortex, 7(4), 374-385.

Gobet, F., & Campitelli, G. (2007). The role of domain-specific practice, handedness, and starting age in chess. Developmental Psychology, 43(1), 159.

Grand, K. F., Bruzi, A. T., Dyke, F. B., Godwin, M. M., Leiker, A. M., Thompson, A. G., . . . Miller, M. W. (2015). Why self-controlled feedback enhances motor learning: Answers from electroencephalography and indices of motivation. Human Movement Science, 43, 23-32.

Guadagnoli, M. A., & Lee, T. D. (2004). Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. Journal of Motor Behavior, 36(2), 212-224.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in Psychology, 52, 139-183.

Hartman, J. M. (2007). Self-controlled use of a perceived physical assistance device during a balancing task. Perceptual and Motor Skills, 104(3), 1005-1016.

Hatfield, B. D., Haufler, A. J., Hung, T.-M., & Spalding, T. W. (2004). Electroencephalographic studies of skilled psychomotor performance. Journal of Clinical Neurophysiology, 21(3), 144-156.

Hatfield, B. D., & Hillman, C. H. (2001). The psychophysiology of sport. In R. N. Singer, H. A. Hausenblas & C. M. Janelle (Eds.), The Handbook of Research on Sport Psychology (2nd ed., pp. 319-339). New York: John Wiley.

Haufler, A. J., Spalding, T. W., Santa Maria, D., & Hatfield, B. D. (2000). Neuro-cognitive activity during a self-paced visuospatial task: comparative EEG profiles in marksmen and novice shooters. Biological Psychology, 53(2), 131-160.

Hayes, A. F. (2013). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach: Guilford Press.

Janelle, C. M., Hillman, C. H., Apparies, R. J., Murray, N. P., Meili, L., Fallon, E. A., & Hatfield, B. D. (2000). Expertise differences in cortical activation and gaze behavior during rifle shooting. Journal of Sport and Exercise Psychology, 22(2), 167-182.

Janelle, C. M., Kim, J., & Singer, R. N. (1995). Subject-controlled performance feedback and learning of a closed motor skill. Perceptual and Motor Skills, 81(2), 627-634.

Janosz, M. (2012). Part IV commentary: Outcomes of engagement and engagement as an outcome: Some consensus, divergences, and unanswered questions Handbook of research on student engagement (pp. 695-703): Springer.

Jaquess, K. J., Lo, L. C., Oh, H., Lu, C., Ginsberg, A., Tan, Y. Y., . . . Gentili, R. J.

(Under revision). Changes in mental workload and motor performance throughout multiple practice sessions under various levels of task difficulty. Neuroscience.

Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. European Journal of Neuroscience, 15(8), 1395-1399.

Kahneman, D. (1973). Attention and Effort: Citeseer.

Keetch, K. M., & Lee, T. D. (2007). The effect of self-regulated and experimenter-imposed practice schedules on motor learning for tasks of varying difficulty. Research Quarterly for Exercise and Sport, 78(5), 476-486.

Kerick, S. E., Douglass, L. W., & Hatfield, B. D. (2004). Cerebral cortical adaptations associated with visuomotor practice. Medicine & Science in Sports & Exercise, 36(1), 118-129.

Kirk, I. J., & Mackay, J. C. (2003). The role of theta-range oscillations in synchronising and integrating activity in distributed mnemonic networks. Cortex, 39(4-5), 993-1008.

Klimesch, W. (1996). Memory processes, brain oscillations and EEG synchronization. International Journal of Psychophysiology, 24(1), 61-100.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Research Reviews, 29(2–3), 169-195. doi: http://dx.doi.org/10.1016/S0165-0173(98)00056-3

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. Trends in Cognitive Sciences, 16(12), 606-617.

Klimesch, W., Doppelmayr, M., Pachinger, T., & Ripper, B. (1997). Brain oscillations and human memory: EEG correlates in the upper alpha and theta band. Neuroscience Letters, 238(1), 9-12.

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: the inhibition–timing hypothesis. Brain Research Reviews, 53(1), 63-88.

Landers, D. M., Han, M., Salazar, W., & Petruzzello, S. J. (1994). Effects of learning on electroencephalographic and electrocardiographic patterns in novice archers. International Journal of Sport Psychology.

Li, Y., Ma, Z., Lu, W., & Li, Y. (2006). Automatic removal of the eye blink artifact from EEG using an ICA-based template matching approach. Physiological Measurement, 27(4), 425.

Luu, P., Tucker, D. M., & Makeig, S. (2004). Frontal midline theta and the error-related negativity: neurophysiological mechanisms of action regulation. Clinical Neurophysiology, 115(8), 1821-1835.

Mathewson, K. E., Lleras, A., Beck, D. M., Fabiani, M., Ro, T., & Gratton, G. (2011). Pulsed out of awareness: EEG alpha oscillations represent a pulsed-inhibition of ongoing cortical processing. Frontiers in Psychology, 2, 99.

Maxwell, J., Masters, R., & Eves, F. (2003). The role of working memory in motor learning and performance. Consciousness and Cognition, 12(3), 376-402.

McLean, J. F., & Hitch, G. J. (1999). Working memory impairments in children with specific arithmetic learning difficulties. Journal of Experimental Child Psychology, 74(3), 240-260.

Mizuhara, H., & Yamaguchi, Y. (2007). Human cortical circuits for central executive function emerge by theta phase synchronization. Neuroimage, 36(1), 232-244.

Myers, N. D., & Feltz, D. L. (2007). From self-efficacy to collective efficacy in sport. Handbook of sport psychology (3rd ed.). John Wiley & Sons: New Jersey, 799-819.

Niedermeyer, E., Naidu, S. B., & Plate, C. (1997). Unusual EEG theta rhythms over central region in Rett syndrome: considerations of the underlying dysfunction. Clinical Electroencephalography, 28(1), 36-43.

O'Reilly, R. C., & Frank, M. J. (2006). Making working memory work: a computational model of learning in the prefrontal cortex and basal ganglia. Neural Computation, 18(2), 283-328.

Pachman, M., Sweller, J., & Kalyuga, S. (2013). Levels of knowledge and deliberate practice. Journal of Experimental Psychology, 19(2), 108-119.

Payne, L., & Kounios, J. (2009). Coherent oscillatory networks supporting short-term memory retention. Brain Research, 1247, 126-132.

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self-regulated learning. International Journal of Educational Research, 31(6), 459-470.

Plank, M. (2013). Ocular correction ICA. Brain Product Press Release, 49, 1-4.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. Journal of Management, 12(4), 531-544.

Rietschel, J. C., McDonald, C. G., Goodman, R. N., Miller, M. W., Jones-Lush, L. M., Wittenberg, G. F., & Hatfield, B. D. (2014). Psychophysiological support of increasing attentional reserve during the development of a motor skill.

Biological Psychology, 103, 349-356.

Rowe, J. P., Shores, L. R., Mott, B. W., & Lester, J. C. (2010). Integrating learning and engagement in narrative-centered learning environments. Paper presented at the International Conference on Intelligent Tutoring Systems.

Sanli, E. A., Patterson, J. T., Bray, S. R., & Lee, T. D. (2012). Understanding self-controlled motor learning protocols through the self-determination theory. Frontiers in Psychology, 3.

Sarter, M., Gehring, W. J., & Kozak, R. (2006). More attention must be paid: the neurobiology of attentional effort. Brain Research Reviews, 51(2), 145-160.

Sauseng, P., Griesmayr, B., Freunberger, R., & Klimesch, W. (2010). Control mechanisms in working memory: a possible function of EEG theta oscillations. Neuroscience & Biobehavioral Reviews, 34(7), 1015-1022.

Sauseng, P., Hoppe, J., Klimesch, W., Gerloff, C., & Hummel, F. C. (2007). Dissociation of sustained attention from central executive functions: local activity and interregional connectivity in the theta range. European Journal of Neuroscience, 25(2), 587-593.

Sauseng, P., Klimesch, W., Schabus, M., & Doppelmayr, M. (2005). Fronto-parietal EEG coherence in theta and upper alpha reflect central executive functions of working memory. International Journal of Psychophysiology, 57(2), 97-103.

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. Psychological Review, 82(4), 225.

Seidler, R. D., Bo, J., & Anguera, J. A. (2012). Neurocognitive contributions to motor skill learning: the role of working memory. Journal of Motor Behavior, 44(6), 445-453.

Silverman, S. (1985). Relationship of engagement and practice trials to student achievement. Journal of Teaching in Physical Education, 5(1), 13-21.

Simon, H. A., & Chase, W. G. (1973). Skill in chess. American Scientist, 61, 394-403.

Smith, M. E., McEvoy, L. K., & Gevins, A. (1999). Neurophysiological indices of strategy development and skill acquisition. Cognitive Brain Research, 7(3), 389-404.

Springer, S. P., & Deutsch, G. (1998). Left brain, right brain: Perspectives from cognitive neuroscience: WH Freeman/Times Books/Henry Holt & Co.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12(2), 257-285. doi: http://dx.doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2010). Element Interactivity and Intrinsic, Extraneous, and Germane Cognitive Load. Educational Psychology Review, 22(2), 123-138. doi: 10.1007/s10648-010-9128-5

Vigneau, M., Beaucousin, V., Herve, P.-Y., Duffau, H., Crivello, F., Houde, O., . . . Tzourio-Mazoyer, N. (2006). Meta-analyzing left hemisphere language areas: phonology, semantics, and sentence processing. Neuroimage, 30(4), 1414-1432.

Ward, P., Hodges, N. J., Williams, A. M., & Starkes, J. L. (2004). Deliberate practice and expert performance Skill acquisition in sport: Research, theory and practice (pp. 231): Routledge.

Wulf, G. (2007). Self-controlled practice enhances motor learning: implications for physiotherapy. Physiotherapy, 93(2), 96-101.

Wulf, G., Raupach, M., & Pfeiffer, F. (2005). Self-controlled observational practice enhances learning. Research Quarterly for Exercise and Sport, 76(1), 107-111.

Wulf, G., & Toole, T. (1999). Physical assistance devices in complex motor skill learning: Benefits of a self-controlled practice schedule. Research Quarterly for Exercise and Sport, 70(3), 265-272.

Yeo, G. B., & Neal, A. (2004). A multilevel analysis of effort, practice, and performance: effects; of ability, conscientiousness, and goal orientation. Journal of Applied Psychology, 89(2), 231.

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. Contemporary Educational Psychology, 25(1), 82-91.

Zusho, A., Pintrich, P. R., & Coppola, B. (2003). Skill and will: The role of motivation and cognition in the learning of college chemistry. International Journal of Science Education, 25(9), 1081-1094.

Chapter 7: General Conclusion

The program of research presented in this dissertation has investigated how various elements of information processing impact cognitive-motor learning and performance. Study one (Jaquess et al., 2017) provided empirical support for the classic theoretical notion that cognitive resources are limited by concurrently measuring mental workload (i.e., resources which are consumed to perform a task) via electroencephalographic (EEG) spectral measures of cortical activation and attentional reserve (i.e., resources which are left over to process other information) via amplitudes of the event-related potential generated by the presentation of "novel" task-irrelevant sounds. It was observed that as task demand increased, so too did mental workload, while attentional reserve was reduced. This observation was the first empirical evidence of a negative relationship between mental workload and attentional reserve, providing direct and objective support for the intuitive notion that humans are limited cognitive processors.

Study two (Jaquess et al., Under revision) expanded upon this work by investigating concurrently the effects of task difficulty and practice on mental workload as indicated by EEG spectral measures of cortical activation. Despite expectations that learning rate, as referenced by both performance improvement and reductions/refinements in cortical activation, would be impacted by task difficulty, learning occurred at similar rates for both relatively easy and hard levels of difficulty. This unexpected finding was explained by the fact that, given the task used in study two was quite complex (operating a flight simulator), both relatively easy and hard difficulties were likely considered similar in difficulty to our novice participants. In order to better assess the impacts of task difficulty and practice on cognitive-motor skill learning and mental workload, a more effective manipulation of task difficulty would need to be employed.

Finally, study three sought to further investigate how cognitive-motor skill learning, from a neuro-cognitive perspective, is impacted by practice. Rather than using an externally-controlled manipulation of practice difficulty, which may or may not be effective at manipulating individually-perceived difficulty (i.e., functional difficulty; (Guadagnoli & Lee, 2004)), self-control of practice difficulty was employed. Self-controlled practice, specifically related to practice difficulty, has been shown to be more effective than externally-controlled practice at promoting skill retention and transfer (Andrieux, Boutin, & Thon, 2016; Andrieux, Danna, & Thon, 2012). Such results imply that learners participating in self-controlled practice are more effectively challenging themselves (Guadagnoli & Lee, 2004), and are more engaged in the task (Wulf, 2007), than their counterparts participating in externally-controlled practice. Results from study three provided evidence that self-controlled practice can be more effective than externally-controlled (yoked) practice in promoting cognitive-motor skill learning. Furthermore, the self-controlled group exhibited greater engagement during practice as indicated by elevated working memory engagement as represented by EEG theta power (Jensen & Tesche, 2002; Sauseng, Griesmayr, Freunberger, & Klimesch, 2010) and greater central executive activity as represented by EEG theta coherence (Anguera et al., 2013; Mizuhara & Yamaguchi, 2007; Payne & Kounios, 2009; Sauseng, Klimesch, Schabus, & Doppelmayr, 2005) relative to the yoked practice group. These observations in a novice sample over a relatively limited practice schedule during which little progress in skill would be expected provide support that neurocognitive engagement as indicated by EEG spectral measures of cortical activation is a potential mechanism underlying the effectiveness of self-controlled practice.

Overall, these results provide support that neuro-cognitive processes impact not only to skilled performance, but also cognitive-motor skill learning. While it has been shown that skilled performance, especially at very high levels, is often defined by a relative lack of cognitive activity (Deeny, Haufler, Saffer, & Hatfield, 2009; Haufler, Spalding, Santa Maria, & Hatfield, 2000; Janelle et al., 2000), here we provide evidence that effective learning, at least during early stages, is aided by relatively great amounts of cognitive activity related to task engagement and the processing of task-relevant information. Indeed, Fitts and Posner (1967) posed that in the first stage of learning, the cognitive stage, that individuals are effortfully engaged in task performance, implying that the brain is in a more active state relative to later stages of learning.

However, much work remains to be done. First, regarding the neurocognitive processes of skill acquisition, assumptions are often made based on findings from comparisons of experts and novices (Hatfield & Hillman, 2001), but little empirical longitudinal data exist to verify these assumptions. To better understand the neuro-cognitive process of cognitive-motor skill learning, and ultimately the acquisition of expertise, it is critical to monitor the cortical dynamics of learners throughout that process. As it can be considered impractical, at best, to collect EEG from a substantial number of participants over the course of the many years it takes to achieve a high level, the use of a relatively constrained task is suggested.

Second, while self-controlled practice may be an effective methodology to enhance learning, it is impacted by a range of psychological elements (Badami, Vaez Mousavi, Wulf, & Namazizadeh, 2012; Bandura & Schunk, 1981; Fisher & Ford, 1998; Wulf, 2007; Yeo & Neal, 2004; Zimmerman, 2000), many of which were controlled in this research program's study three. Given the wide range of potential confounds and other short-comings inherent to self-controlled practice, future work may consider augmentations to the method. For example, while self-controlled practice may allow learners to challenge themselves more effectively, it is unknown if the level chosen is "optimal" for that individual (Guadagnoli & Lee, 2004). Future work may consider applying small deviations to a self-elected level of difficulty, in an effort to see if individuals performing self-controlled practice tend to under- or over-challenge themselves (Atkinson & Feather, 1966; Maehr & Zusho, 2009; Weiss & Chaumeton, 1992) and what factors influence that choice.

References

Andrieux, M., Boutin, A., & Thon, B. (2016). Self-control of task difficulty during early practice promotes motor skill learning. Journal of Motor Behavior, 48(1), 57-65.

Andrieux, M., Danna, J., & Thon, B. (2012). Self-control of task difficulty during training enhances motor learning of a complex coincidence-anticipation task. Research Quarterly for Exercise and Sport, 83(1), 27-35.

Anguera, J. A., Boccanfuso, J., Rintoul, J. L., Al-Hashimi, O., Faraji, F., Janowich, J., . . . Johnston, E. (2013). Video game training enhances cognitive control in older adults. Nature, 501(7465), 97-101.

Atkinson, J. W., & Feather, N. T. (1966). A theory of achievement motivation (Vol. 66): Wiley New York.

Badami, R., Vaez Mousavi, M., Wulf, G., & Namazizadeh, M. (2012). Feedback about more accurate versus less accurate trials: Differential effects on self-confidence and activation. Research Quarterly for Exercise and Sport, 83(2), 196-203.

Bandura, A., & Schunk, D. H. (1981). Cultivating competence, self-efficacy, and intrinsic interest through proximal self-motivation. Journal of Personality and Social Psychology, 41(3), 586.

Deeny, S. P., Haufler, A. J., Saffer, M., & Hatfield, B. D. (2009). Electroencephalographic coherence during visuomotor performance: a comparison of cortico-cortical communication in experts and novices. Journal of Motor Behavior, 41(2), 106-116.

Fisher, S. L., & Ford, J. K. (1998). Differential effects of learner effort and goal orientation on two learning outcomes. Personnel Psychology, 51(2), 397-420.

Fitts, P. M., & Posner, M. I. (1967). Human Performance. Oxford, England: Brooks/Cole.

Guadagnoli, M. A., & Lee, T. D. (2004). Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. Journal of Motor Behavior, 36(2), 212-224.

Hatfield, B. D., & Hillman, C. H. (2001). The psychophysiology of sport. In R. N. Singer, H. A. Hausenblas & C. M. Janelle (Eds.), The Handbook of Research on Sport Psychology (2nd ed., pp. 319-339). New York: John Wiley.

Haufler, A. J., Spalding, T. W., Santa Maria, D., & Hatfield, B. D. (2000). Neuro-cognitive activity during a self-paced visuospatial task: comparative EEG profiles in marksmen and novice shooters. Biological Psychology, 53(2), 131-160.

Janelle, C. M., Hillman, C. H., Apparies, R. J., Murray, N. P., Meili, L., Fallon, E. A., & Hatfield, B. D. (2000). Expertise differences in cortical activation and gaze behavior during rifle shooting. Journal of Sport and Exercise Psychology, 22(2), 167-182.

Jaquess, K. J., Gentili, R. J., Lo, L. C., Oh, H., Zhang, J., Rietschel, J. C., . . . Hatfield, B. D. (2017). Empirical evidence for the relationship between cognitive workload and attentional reserve. International Journal of Psychophysiology, 121, 46-55. doi: https://doi.org/10.1016/j.ijpsycho.2017.09.007

Jaquess, K. J., Lo, L. C., Oh, H., Lu, C., Ginsberg, A., Tan, Y. Y., . . . Gentili, R. J. (Under revision). Changes in mental workload and motor performance throughout multiple practice sessions under various levels of task difficulty. Neuroscience.

Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. European Journal of Neuroscience, 15(8), 1395-1399.

Maehr, M. L., & Zusho, A. (2009). Achievement goal theory. Handbook of Motivation at School, 77-104.

Mizuhara, H., & Yamaguchi, Y. (2007). Human cortical circuits for central executive function emerge by theta phase synchronization. Neuroimage, 36(1), 232-244.

Payne, L., & Kounios, J. (2009). Coherent oscillatory networks supporting short-term memory retention. Brain Research, 1247, 126-132.

Sauseng, P., Griesmayr, B., Freunberger, R., & Klimesch, W. (2010). Control mechanisms in working memory: a possible function of EEG theta oscillations. Neuroscience & Biobehavioral Reviews, 34(7), 1015-1022.

Sauseng, P., Klimesch, W., Schabus, M., & Doppelmayr, M. (2005). Fronto-parietal EEG coherence in theta and upper alpha reflect central executive functions of working memory. International Journal of Psychophysiology, 57(2), 97-103.

Weiss, M., & Chaumeton, N. (1992). Motivational orientations in sport. In T. S. Horn (Ed.), Advances in Sport Psychology (pp. 61-99). Champagne, IL: Human Kinetics.

Wulf, G. (2007). Self-controlled practice enhances motor learning: implications for physiotherapy. Physiotherapy, 93(2), 96-101.

Yeo, G. B., & Neal, A. (2004). A multilevel analysis of effort, practice, and performance: effects; of ability, conscientiousness, and goal orientation. Journal of Applied Psychology, 89(2), 231.

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. Contemporary Educational Psychology, 25(1), 82-91.

Appendices

Appendix A.
Basic Instructions

This experiment is interested in how we learn motor skills. As such, there will be an initial assessment of skill to acquire your baseline level of performance at putting. The baseline test will consist of 10 putts at a putting distance of 5 feet. This will subsequently be followed by a period of practice. Practice will be conducted at any distance from the target, up to 10 feet. Each day after the practice sessions, you will be asked to perform a second baseline test of 10 putts at a distance of 5 ft. On the final visit, you will be given a retention test which will be used to gauge your improvement in the skill of putting. The retention test will consist of 10 putts at a set distance within the pre-specified practice range. As an added incentive to learn the task as best as possible, a bonus of $50 will be granted to the participant with the highest number of successful putts during the retention test among all participants within his/her experimental group.

During the experiment, please putt as you would naturally. The putting task in this experiment is more-or-less self-paced. When you are ready to putt, please get into your ready position and remain stationary in the ready position for at approximately 5 seconds prior to executing a putt. After this 5 second period you may execute the putt. I will let you know how many putts you have left in a given block in increments of 5 (so 20 putts left, 15 putts left, 10 putts left, and so on). Please do your best on every putt. Any questions?

Baseline

We will now begin the baseline performance session. This session will consist of 10 putts at a distance of 5 feet. Please do your best to sink as many putts as you can. Again, remain stationary in the ready position for at approximately 5 seconds prior to executing a putt. Any questions?

PRACTICE (Self-Controlled)

We will now begin the practice blocks. There will be two blocks today of 40 putts. Feel free to choose the distance you would like to putt at prior to initiating a putt. Please structure your practice to optimize your learning so you can perform as well as possible during the retention test. Again, remain stationary in the ready position for approximately 5 seconds prior to executing a putt. Any questions?

PRACTICE (Yoked)

We will now begin the practice blocks. There will be two blocks today of 40 putts. The distance of each putt may or may not be changed between each putt. Please try your best to learn the task during these practice trials so you can perform as well as possible during the retention test. Again, remain stationary in the ready position for at approximately 5 seconds prior to executing a putt. Any questions?

Appendix B.

How to conduct the test

- The assistant explains the test protocol to the athlete:
    - Consider the statement "I feel most successful in sport when…" and read each of the questions on the questionnaire below and indicate how much you personally agree with each statement by entering an appropriate score where:
    - 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree

- The athlete completes the questionnaire - no time limit
- The assistant determines and records the athlete's TEOSQ scores

The Ego and Task orientation results are calculated are as follows (q=question):

•Ego Orientation = (q1 + q3 + q4 + q6 + q9 + q11) ÷ 6

•Task Orientation = (q2 + q5 + q7 + q8 + q10 + q12 + q13) ÷ 7

Task and Ego Orientation in Sport Questionnaire (TEOSQ) (Duda 1989)

How to conduct the test

Consider the statement "I feel most successful in sport when…" and read each of the questions on the questionnaire below and indicate how much you personally agree with each statement by entering an appropriate score where:

1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree

I feel most successful in sport when…

1) I am the only one who can do the play or the skill.
1 2 3 4 5

2) I learn a new skill and it makes me want to practice more.
1 2 3 4 5

3) I can do better that my friends.
1 2 3 4 5

4) The others cannot do as well as me.
1 2 3 4 5

5) I learn something that is fun to do.
1 2 3 4 5

6) Others mess up but I do not.
1 2 3 4 5

7) I learn a new skill by trying hard.
1 2 3 4 5

8) I work really hard.
1 2 3 4 5

9) I score the most points/goals/hits, etc.
1 2 3 4 5

10) Something I learn makes me want to go practice more.

1	2	3	4	5

11) I am the best.

1	2	3	4	5

12) A skill I learn really feels right.

1	2	3	4	5

13) I do my very best.

1	2	3	4	5

Appendix C.

Self-Efficacy Inventory
Please circle "YES" or "NO" in response to the statements below. If answered "YES", please write in the predicted percentage of success (0-100%) for that statement.

1) I have the skills and resources to successfully putt the ball from 1 foot.
YES NO
If yes, percentage of success:____________

2) I have the skills and resources to successfully putt the ball from 2 feet.
YES NO
If yes, percentage of success:____________

3) I have the skills and resources to successfully putt the ball from 3 feet.
YES NO
If yes, percentage of success:____________

4) I have the skills and resources to successfully putt the ball from 4 feet.
YES NO
If yes, percentage of success:____________

5) I have the skills and resources to successfully putt the ball from 5 feet.
YES NO
If yes, percentage of success:____________

6) I have the skills and resources to successfully putt the ball from 6 feet.
YES NO
If yes, percentage of success:____________

7) I have the skills and resources to successfully putt the ball from 7 feet.
YES NO
If yes, percentage of success:____________

8) I have the skills and resources to successfully putt the ball from 8 feet.
YES NO
If yes, percentage of success:____________

9) I have the skills and resources to successfully putt the ball from 9 feet.
YES NO
If yes, percentage of success:____________

10) I have the skills and resources to successfully putt the ball from 10 feet.
YES NO
If yes, percentage of success:____________

Appendix D.

How confident are you in your ability to perform the task successfully?

Not at all confident Very confident

Appendix E.

How motivated were you during practice to learn the task?

Not at all motivated | Very motivated

Appendix F.

How motivated were you to perform to the best of your ability during the task?

Not at all motivated | Very motivated

Appendix G.

Figure 8.6

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low — Very High

Appendix H.

How interested were you in this experiment?

Not at all interested | Very interested

Bibliography

Akizuki, K., & Ohashi, Y. (2015). Measurement of functional task difficulty during motor learning: What level of difficulty corresponds to the optimal challenge point? Human Movement Science, 43, 107-117.

Allison, B. Z., & Polich, J. (2008). Workload assessment of computer gaming using a single-stimulus event-related potential paradigm. Biological psychology, 77(3), 277-283.

Andrieux, M., Boutin, A., & Thon, B. (2016). Self-control of task difficulty during early practice promotes motor skill learning. Journal of motor behavior, 48(1), 57-65.

Andrieux, M., Danna, J., & Thon, B. (2012). Self-control of task difficulty during training enhances motor learning of a complex coincidence-anticipation task. Research quarterly for exercise and sport, 83(1), 27-35.

Anguera, J. A., Boccanfuso, J., Rintoul, J. L., Al-Hashimi, O., Faraji, F., Janowich, J., . . . Johnston, E. (2013). Video game training enhances cognitive control in older adults. nature, 501(7465), 97-101.

Atkinson, J. W., & Feather, N. T. (1966). A theory of achievement motivation (Vol. 66): Wiley New York.

Ayaz, H., Shewokis, P. A., Bunce, S., Izzetoglu, K., Willems, B., & Onaral, B. (2012). Optical brain monitoring for operator training and mental workload assessment. Neuroimage, 59(1), 36-47.

Ayaz, H., Willems, B., Bunce, B., Shewokis, P. A., Izzetoglu, K., Hah, S., . . . Onaral, B. (2010). Cognitive workload assessment of air traffic controllers using optical brain imaging sensors. Advances in understanding human performance: Neuroergonomics, human factors design, and special populations, 21-31.

Badami, R., Vaez Mousavi, M., Wulf, G., & Namazizadeh, M. (2012). Feedback about more accurate versus less accurate trials: Differential effects on self-confidence and activation. Research quarterly for exercise and sport, 83(2), 196-203.

Baddeley, A. (2012). Working memory: theories, models, and controversies. Annual Review of Psychology, 63, 1-29.

Bandura, A., & Schunk, D. H. (1981). Cultivating competence, self-efficacy, and intrinsic interest through proximal self-motivation. Journal of personality and social psychology, 41(3), 586.

Başar, E., Schürmann, M., & Sakowitz, O. (2001). The selectively distributed theta system: functions. International Journal of Psychophysiology, 39(2), 197-212. doi: https://doi.org/10.1016/S0167-8760(00)00141-0

Basile, L. F., Anghinah, R., Ribeiro, P., Ramos, R. T., Piedade, R., Ballester, G., & Brunetti, E. P. (2007). Interindividual variability in EEG correlates of attention and limits of functional mapping. International Journal of Psychophysiology, 65(3), 238-251.

Baumeister, J., Reinecke, K., Liesen, H., & Weiss, M. (2008). Cortical activity of skilled performance in a complex sports related motor task. European journal of applied physiology, 104(4), 625-631.

Binder, J. R., Frost, J. A., Hammeke, T. A., Cox, R. W., Rao, S. M., & Prieto, T. (1997). Human brain language areas identified by functional magnetic resonance imaging. Journal of Neuroscience, 17(1), 353-362.

Boutin, A., Badets, A., Salesse, R. N., Fries, U., Panzer, S., & Blandin, Y. (2012). Practice makes transfer of motor skills imperfect. Psychological research, 76(5), 611-625.

Boutin, A., Blandin, Y., Massen, C., Heuer, H., & Badets, A. (2014). Conscious awareness of action potentiates sensorimotor learning. Cognition, 133(1), 1-9.

Boutin, A., Panzer, S., & Blandin, Y. (2013). Retrieval practice in motor learning. Human Movement Science, 32(6), 1201-1213.

Boutin, A., Pinsard, B., Boré, A., Carrier, J., Fogel, S. M., & Doyon, J. (2017). Transient synchronization of hippocampo-striato-thalamo-cortical networks during sleep spindle oscillations induces motor memory consolidation. Neuroimage.

Broadbent, D. E. (1957). A mechanical model for human attention and immediate memory. Psychological review, 64(3), 205.

Brookings, J. B., Wilson, G. F., & Swain, C. R. (1996). Psychophysiological responses to changes in workload during simulated air traffic control. Biological psychology, 42(3), 361-377.

Brouwer, A.-M., Hogervorst, M. A., Van Erp, J. B., Heffelaar, T., Zimmerman, P. H., & Oostenveld, R. (2012). Estimating workload using EEG spectral power and ERPs in the n-back task. Journal of neural engineering, 9(4), 045008.

Budzynski, T. H., Budzynski, H. K., Evans, J. R., & Abarbanel, A. (2009). Introduction to quantitative EEG and neurofeedback: Advanced theory and applications: Academic Press.

Caplan, J. B., Madsen, J. R., Schulze-Bonhage, A., Aschenbrenner-Scheibe, R., Newman, E. L., & Kahana, M. J. (2003). Human θ oscillations related to sensorimotor integration and spatial learning. Journal of Neuroscience, 23(11), 4726-4736.

Carini, R. M., Kuh, G. D., & Klein, S. P. (2006). Student engagement and student learning: Testing the linkages. Research in higher education, 47(1), 1-32.

Cavanagh, J. F., Cohen, M. X., & Allen, J. J. (2009). Prelude to and resolution of an error: EEG phase synchrony reveals cognitive control dynamics during action monitoring. Journal of Neuroscience, 29(1), 98-105.

Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. Trends in cognitive sciences, 18(8), 414-421.

Cavanagh, J. F., Zambrano-Vazquez, L., & Allen, J. J. (2012). Theta lingua franca: A common mid-frontal substrate for action monitoring processes. Psychophysiology, 49(2), 220-238.

Chang, G. H. L. Y. H., & Lin, K. P. (2005). Comparison of heart rate variability measured by ECG in different signal lengths. Journal of Medical and Biological Engineering, 25(2), 67-71.

Cheng, M.-Y., Huang, C.-J., Chang, Y.-K., Koester, D., Schack, T., & Hung, T.-M. (2015). Sensorimotor rhythm neurofeedback enhances golf putting performance. Journal of Sport and Exercise Psychology, 37(6), 626-636.

Cheng, M.-Y., Hung, C.-L., Huang, C.-J., Chang, Y.-K., Lo, L.-C., Shen, C., & Hung, T.-M. (2015). Expert-novice differences in SMR activity during dart throwing. Biological psychology, 110, 212-218.

Chiviacowsky, S., & Wulf, G. (2002). Self-controlled feedback: Does it enhance learning because performers get feedback when they need it? Research quarterly for exercise and sport, 73(4), 408-415.

Cinaz, B., Arnrich, B., La Marca, R., & Tröster, G. (2013). Monitoring of mental workload levels during an everyday life office-work scenario. Personal and ubiquitous computing, 17(2), 229-239.

Clément, R., Dörnyei, Z., & Noels, K. A. (1994). Motivation, self-confidence, and group cohesion in the foreign language classroom. Language learning, 44(3), 417-448.

Costanzo, M. E., VanMeter, J. W., Janelle, C. M., Braun, A., Miller, M. W., Oldham, J., . . . Hatfield, B. D. (2016). Neural efficiency in expert cognitive-motor performers during affective challenge. Journal of motor behavior, 48(6), 573-588.

Cowan, N. (2008). What are the differences between long-term, short-term, and working memory? Progress in brain research, 169, 323-338.

Dayan, E., & Cohen, L. G. (2011). Neuroplasticity subserving motor skill learning. Neuron, 72(3), 443-454.

Deeny, S. P., Haufler, A. J., Saffer, M., & Hatfield, B. D. (2009). Electroencephalographic coherence during visuomotor performance: a comparison of cortico-cortical communication in experts and novices. Journal of motor behavior, 41(2), 106-116.

Deeny, S. P., Hillman, C. H., Janelle, C. M., & Hatfield, B. D. (2003). Cortico-cortical communication and superior performance in skilled marksmen: an EEG coherence analysis. Journal of Sport and Exercise Psychology, 25(2), 188-204.

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of neuroscience methods, 134(1), 9-21.

Doppelmayr, M., Finkenzeller, T., & Sauseng, P. (2008). Frontal midline theta in the pre-shot phase of rifle shooting: differences between experts and novices. Neuropsychologia, 46(5), 1463-1467.

Doppelmayr, M., Klimesch, W., Pachinger, T., & Ripper, B. (1998). Individual differences in brain dynamics: important implications for the calculation of event-related band power. Biological cybernetics, 79(1), 49-57.

Duda, J. L. (1989). Relationship between task and ego orientation and the perceived purpose of sport among high school athletes. Journal of Sport and Exercise Psychology, 11, 318-335.

Dyke, F. B., Leiker, A. M., Grand, K. F., Godwin, M. M., Thompson, A. G., Rietschel, J. C., . . . Miller, M. W. (2015). The efficacy of auditory probes in indexing cognitive workload is dependent on stimulus complexity. International Journal of Psychophysiology, 95(1), 56-62.

Ericsson, K. A. (2008). Deliberate practice and acquisition of expert performance: A general overview. Academic Emergency Medicine, 15(11), 988-994.

Ericsson, K. A., Krampe, R. T., & Tesch-Römer, C. (1993). The role of deliberate practice in the acquisition of sports expertise. Psychological review, 100, 363-406.

Fabiani, M., Kazmerski, V. A., Cycowicz, Y. M., & Friedman, D. (1996). Naming norms for brief environmental sounds: Effects of age and dementia. Psychophysiology, 33(4), 462-475.

Fisher, S. L., & Ford, J. K. (1998). Differential effects of learner effort and goal orientation on two learning outcomes. Personnel Psychology, 51(2), 397-420.

Fitts, P. M., & Posner, M. I. (1967). Human Performance. Oxford, England: Brooks/Cole.

Foxe, J. J., & Snyder, A. C. (2011). The role of alpha-band brain oscillations as a sensory suppression mechanism during selective attention. Frontiers in psychology, 2, 154.

Furley, P., Memmert, D., & Schmid, S. (2013). Perceptual load in sport and the heuristic value of the perceptual load paradigm in examining expertise-related perceptual-cognitive adaptations. Cognitive processing, 14(1), 31-42.

Gentili, R. J., Bradberry, T. J., Oh, H., Hatfield, B. D., & Contreras Vidal, J. L. (2011). Cerebral cortical dynamics during visuomotor transformation: Adaptation to a cognitive-motor executive challenge. Psychophysiology, 48(6), 813-824.

Gentili, R. J., Jaquess, K. J., Shuggi, I. M., Oh, H., Lo, L.-C., Tan, Y. Y., . . . Hatfield, B. D. (Submitted). Assessment of a dry EEG system for multimodal assessment of cognitive workload under various level of challenge: Towards ecological applications in the field.

Gentili, R. J., Jaquess, K. J., Shuggi, I. M., Shaw, E. P., Oh, H., Lo, L. C., . . . Hatfield, B. D. (2018). Combined assessment of attentional reserve and cognitive-motor effort under various levels of challenge with a dry EEG system. . Psychophysiology.

Gentili, R. J., Rietschel, J. C., Jaquess, K. J., Lo, L.-C., Prevost, M., Miller, M. W., . . . Hatfield, B. D. (2014). Brain biomarkers based assessment of cognitive workload in pilots under various task demands. Paper presented at the Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE.

Gentili, R. J., Shewokis, P. A., Ayaz, H., & Contreras-Vidal, J. L. (2013). Functional near-infrared spectroscopy-based correlates of prefrontal cortical dynamics during a cognitive-motor executive adaptation task. Frontiers in human neuroscience, 7.

Gevins, A., & Smith, M. E. (1999). Detecting transient cognitive impairment with EEG pattern recognition methods. Aviation, space, and environmental medicine, 70(10), 1018-1024.

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. Theoretical Issues in Ergonomics Science, 4(1-2), 113-131.

Gevins, A., Smith, M. E., McEvoy, L., & Yu, D. (1997). High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. Cerebral Cortex, 7(4), 374-385.

Gobet, F., & Campitelli, G. (2007). The role of domain-specific practice, handedness, and starting age in chess. Developmental Psychology, 43(1), 159.

Gola, M., Magnuski, M., Szumska, I., & Wróbel, A. (2013). EEG beta band activity is related to attention and attentional deficits in the visual performance of elderly subjects. International Journal of Psychophysiology, 89(3), 334-341.

Grand, K. F., Bruzi, A. T., Dyke, F. B., Godwin, M. M., Leiker, A. M., Thompson, A. G., . . . Miller, M. W. (2015). Why self-controlled feedback enhances motor learning: Answers from electroencephalography and indices of motivation. Human Movement Science, 43, 23-32.

Guadagnoli, M. A., & Lee, T. D. (2004). Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. Journal of motor behavior, 36(2), 212-224.

Haider, H., & Frensch, P. A. (1999). Eye movement during skill acquisition: More evidence for the information-reduction hypothesis. Journal of Experimental Psychology: Learning, Memory, and Cognition, 25(1), 172.

Hankins, T. C., & Wilson, G. F. (1998). A comparison of heart rate, eye activity, EEG and subjective measures of pilot mental workload during flight. Aviation, space, and environmental medicine, 69(4), 360-367.

Hansen, J. C., & Hillyard, S. A. (1980). Endogeneous brain potentials associated with selective auditory attention. Electroencephalography and clinical neurophysiology, 49(3), 277-290.

Hanslmayr, S., Klimesch, W., Sauseng, P., Gruber, W., Doppelmayr, M., Freunberger, R., & Pecherstorfer, T. (2005). Visual discrimination performance is related to decreased alpha amplitude but increased phase locking. Neuroscience letters, 375(1), 64-68.

Hart, S. G. (2006). NASA-task load index (NASA-TLX); 20 years later. Paper presented at the Proceedings of the human factors and ergonomics society annual meeting.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in psychology, 52, 139-183.

Hartman, J. M. (2007). Self-controlled use of a perceived physical assistance device during a balancing task. Perceptual and motor skills, 104(3), 1005-1016.

Hatfield, B. D., & Hillman, C. H. (2001). The psychophysiology of sport. In R. N. Singer, H. A. Hausenblas & C. M. Janelle (Eds.), The Handbook of Research on Sport Psychology (2nd ed., pp. 319-339). New York: John Wiley.

Haufler, A. J., Spalding, T. W., Santa Maria, D., & Hatfield, B. D. (2000). Neuro-cognitive activity during a self-paced visuospatial task: comparative EEG profiles in marksmen and novice shooters. Biological psychology, 53(2), 131-160.

Hayes, A. F. (2013). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach: Guilford Press.

Herholz, S. C., & Zatorre, R. J. (2012). Musical training as a framework for brain plasticity: behavior, function, and structure. Neuron, 76(3), 486-502.

Hockey, G. R. J., Nickel, P., Roberts, A. C., & Roberts, M. H. (2009). Sensitivity of candidate markers of psychophysiological strain to cyclical changes in manual control load during simulated process control. Applied ergonomics, 40(6), 1011-1018.

Holm, A., Lukander, K., Korpela, J., Sallinen, M., & Müller, K. M. (2009). Estimating brain load from the EEG. The Scientific World Journal, 9, 639-651.

Intriligator, J., & Polich, J. (1994). On the relationship between background EEG and the P300 event-related potential. Biological psychology, 37(3), 207-218.

Jaiswal, N., Ray, W., & Slobounov, S. (2010). Encoding of visual–spatial information in working memory requires more cerebral efforts than retrieval: Evidence from an EEG and virtual reality study. Brain research, 1347, 80-89.

Janelle, C. M., Hillman, C. H., Apparies, R. J., Murray, N. P., Meili, L., Fallon, E. A., & Hatfield, B. D. (2000). Expertise differences in cortical activation and gaze behavior during rifle shooting. Journal of Sport and Exercise Psychology, 22(2), 167-182.

Janelle, C. M., Kim, J., & Singer, R. N. (1995). Subject-controlled performance feedback and learning of a closed motor skill. Perceptual and motor skills, 81(2), 627-634.

Janosz, M. (2012). Part IV commentary: Outcomes of engagement and engagement as an outcome: Some consensus, divergences, and unanswered questions Handbook of research on student engagement (pp. 695-703): Springer.

Jansen, B. H., & Brandt, M. E. (1991). The effect of the phase of prestimulus alpha activity on the averaged visual evoked response. Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section, 80(4), 241-250.

Jaquess, K. J., Gentili, R. J., Lo, L. C., Oh, H., Zhang, J., Rietschel, J. C., . . . Hatfield, B. D. (2017). Empirical evidence for the relationship between cognitive workload and attentional reserve. . International Journal of Psychophysiology, 121, 46-55. doi: https://doi.org/10.1016/j.ijpsycho.2017.09.007

Jaquess, K. J., Lo, L. C., Oh, H., Lu, C., Ginsberg, A., Tan, Y. Y., . . . Gentili, R. J. (Under revision). Changes in mental workload and motor performance throughout multiple practice sessions under various levels of task difficulty. Neuroscience.

Jarodzka, H., Scheiter, K., Gerjets, P., & Van Gog, T. (2010). In the eyes of the beholder: How experts and novices interpret dynamic stimuli. Learning and Instruction, 20(2), 146-154.

Jasper, H. H. (1958). Report of the committee on methods of clinical examination in electroencephalography. Electroencephalography and clinical neurophysiology, 10(2), 370-375. doi: http://dx.doi.org/10.1016/0013-4694(58)90053-1

Jensen, O., Gelfand, J., Kounios, J., & Lisman, J. E. (2002). Oscillations in the alpha band (9–12 Hz) increase with memory load during retention in a short-term memory task. Cerebral Cortex, 12(8), 877-882.

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. Frontiers in human neuroscience, 4, 186.

Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. European journal of Neuroscience, 15(8), 1395-1399.

Jung, T. P., Makeig, S., Westerfield, M., Townsend, J., Courchesne, E., & Sejnowski, T. J. (2001). Analysis and visualization of single-trial event-related potentials. Human brain mapping, 14(3), 166-185.

Kahneman, D. (1973). Attention and effort: Citeseer.

Kanske, P., Plitschka, J., & Kotz, S. A. (2011). Attentional orienting towards emotion: P2 and N400 ERP effects. Neuropsychologia, 49(11), 3121-3129. doi: http://dx.doi.org/10.1016/j.neuropsychologia.2011.07.022

Kantak, S. S., & Winstein, C. J. (2012). Learning–performance distinction and memory processes for motor skills: A focused review and perspective. Behavioural brain research, 228(1), 219-231.

Kantowitz, B. H. (1987). 3. Mental Workload. Advances in psychology, 47, 81-121.

Kerick, S. E., Douglass, L. W., & Hatfield, B. D. (2004). Cerebral cortical adaptations associated with visuomotor practice. Medicine & Science in Sports & Exercise, 36(1), 118-129.

Kirk, I. J., & Mackay, J. C. (2003). The role of theta-range oscillations in synchronising and integrating activity in distributed mnemonic networks. Cortex, 39(4-5), 993-1008.

Klimesch, W. (1996). Memory processes, brain oscillations and EEG synchronization. International Journal of Psychophysiology, 24(1), 61-100.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain research reviews, 29(2–3), 169-195. doi: http://dx.doi.org/10.1016/S0165-0173(98)00056-3

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. Trends in cognitive sciences, 16(12), 606-617.

Klimesch, W., Doppelmayr, M., Pachinger, T., & Ripper, B. (1997). Brain oscillations and human memory: EEG correlates in the upper alpha and theta band. Neuroscience letters, 238(1), 9-12.

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: the inhibition–timing hypothesis. Brain research reviews, 53(1), 63-88.

Klostermann, F., Nikulin, V. V., Kühn, A. A., Marzinzik, F., Wahl, M., Pogosyan, A., . . . Curio, G. (2007). Task-related differential dynamics of EEG alpha-and beta-band synchronization in cortico-basal motor structures. European journal of Neuroscience, 25(5), 1604-1615.

Krakauer, J. W., & Mazzoni, P. (2011). Human sensorimotor learning: adaptation, skill, and beyond. Current opinion in neurobiology, 21(4), 636-644.

Landers, D. M., Han, M., Salazar, W., & Petruzzello, S. J. (1994). Effects of learning on electroencephalographic and electrocardiographic patterns in novice archers. International Journal of Sport Psychology.

Leiker, A. M., Bruzi, A. T., Miller, M. W., Nelson, M., Wegman, R., & Lohse, K. R. (2016). The effects of autonomous difficulty selection on engagement, motivation, and learning in a motion-controlled video game task. Human Movement Science, 49, 326-335.

Leiker, A. M., Miller, M., Brewer, L., Nelson, M., Siow, M., & Lohse, K. (2016). The Relationship Between Engagement and Neurophysiological Measures of Attention in Motion-Controlled Video Games: A Randomized Controlled Trial. JMIR serious games, 4(1).

Li, Y., Ma, Z., Lu, W., & Li, Y. (2006). Automatic removal of the eye blink artifact from EEG using an ICA-based template matching approach. Physiological measurement, 27(4), 425.

Luu, P., Tucker, D. M., & Makeig, S. (2004). Frontal midline theta and the error-related negativity: neurophysiological mechanisms of action regulation. Clinical neurophysiology, 115(8), 1821-1835.

Maehr, M. L., & Zusho, A. (2009). Achievement goal theory. Handbook of motivation at school, 77-104.

Magill, R. A., & Anderson, D. (2016). Motor Learning and Control: Concepts and Applications (11 ed.). New York: McGraw-Hill Education.

Marteniuk, R. G. (1976). Information processing in motor skills: Holt, Rinehart and Winston.

Mathewson, K. E., Lleras, A., Beck, D. M., Fabiani, M., Ro, T., & Gratton, G. (2011). Pulsed out of awareness: EEG alpha oscillations represent a pulsed-inhibition of ongoing cortical processing. Frontiers in psychology, 2, 99.

Mauri, M., Magagnin, V., Cipresso, P., Mainardi, L., Brown, E. N., Cerutti, S., . . . Barbieri, R. (2010, Aug. 31 2010-Sept. 4 2010). Psychophysiological signals associated with affective states. Paper presented at the 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology.

Maxwell, J., Masters, R., & Eves, F. (2003). The role of working memory in motor learning and performance. Consciousness and Cognition, 12(3), 376-402.

McLean, J. F., & Hitch, G. J. (1999). Working memory impairments in children with specific arithmetic learning difficulties. Journal of experimental child psychology, 74(3), 240-260.

Mehler, B., Reimer, B., & Wang, Y. (2011). A comparison of heart rate and heart rate variability indices in distinguishing single task driving and driving under secondary cognitive workload. Paper presented at the Proc Driving Symposium on Human Factors in Driver Assessment.

Miller, M. W., Rietschel, J. C., McDonald, C. G., & Hatfield, B. D. (2011). A novel approach to the physiological measurement of mental workload. International Journal of Psychophysiology, 80(1), 75-78. doi: http://dx.doi.org/10.1016/j.ijpsycho.2011.02.003

Mizuhara, H., & Yamaguchi, Y. (2007). Human cortical circuits for central executive function emerge by theta phase synchronization. Neuroimage, 36(1), 232-244.

Munoz, M. L., van Roon, A., Riese, H., Thio, C., Oostenbroek, E., Westrik, I., . . . Nolte, I. M. (2015). Validity of (Ultra-) Short Recordings for Heart Rate Variability Measurements. PloS one, 10(9), e0138921.

Myers, N. D., & Feltz, D. L. (2007). From self-efficacy to collective efficacy in sport. Handbook of sport psychology (3rd ed.). John Wiley & Sons: New Jersey, 799-819.

Nassef, A., Mahfouf, M., Linkens, D., Elsamahy, E., Roberts, A., Nickel, P., . . . Panoutsos, G. (2009). The assessment of Heart Rate Variability (HRV) and Task Load Index (TLI) as physiological markers for physical stress. Paper presented at the World Congress on Medical Physics and Biomedical Engineering, September 7-12, 2009, Munich, Germany.

Niedermeyer, E., Naidu, S. B., & Plate, C. (1997). Unusual EEG theta rhythms over central region in Rett syndrome: considerations of the underlying dysfunction. Clinical electroencephalography, 28(1), 36-43.

O'Reilly, R. C., & Frank, M. J. (2006). Making working memory work: a computational model of learning in the prefrontal cortex and basal ganglia. Neural computation, 18(2), 283-328.

Pachman, M., Sweller, J., & Kalyuga, S. (2013). Levels of knowledge and deliberate practice. Journal of Experimental Psychology, 19(2), 108-119.

Palinko, O., Kun, A. L., Shyrokov, A., & Heeman, P. (2010). Estimating cognitive load using remote eye tracking in a driving simulator. Paper presented at the Proceedings of the 2010 Symposium on Eye-Tracking Research & Applications.

Payne, L., & Kounios, J. (2009). Coherent oscillatory networks supporting short-term memory retention. Brain research, 1247, 126-132.

Perfetti, B., Moisello, C., Landsness, E. C., Kvint, S., Lanzafame, S., Onofrj, M., . . . Ghilardi, M. F. (2011). Modulation of gamma and theta spectral amplitude and phase synchronization is associated with the development of visuo-motor learning. Journal of Neuroscience, 31(41), 14810-14819.

Picton, T., & Hillyard, S. (1974). Human auditory evoked potentials. II: Effects of attention. Electroencephalography and clinical neurophysiology, 36, 191-200.

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self-regulated learning. International journal of educational research, 31(6), 459-470.

Plank, M. (2013). Ocular correction ICA. Brain Product Press Release, 49, 1-4.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. Journal of management, 12(4), 531-544.

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. Clinical neurophysiology, 118(10), 2128-2148.

Postma, M. A., Schellekens, J., Hanson, E. K., & Hoogeboom, P. J. (2005). Fz theta divided by Pz alpha as an index of task load during a PC-based air traffic control simulation (pp. 1-5): Shaker Publishing, Maastricht, The Netherlands.

Ray, W. J., & Cole, H. W. (1985). EEG alpha activity reflects attentional demands, and beta activity reflects emotional and cognitive processes. Science, 228, 750-752.

Rietschel, J. C., McDonald, C. G., Goodman, R. N., Miller, M. W., Jones-Lush, L. M., Wittenberg, G. F., & Hatfield, B. D. (2014). Psychophysiological support of increasing attentional reserve during the development of a motor skill. Biological psychology, 103, 349-356.

Rietschel, J. C., Miller, M. W., Gentili, R. J., Goodman, R. N., McDonald, C. G., & Hatfield, B. D. (2012). Cerebral-cortical networking and activation increase as a function of cognitive-motor task difficulty. Biological psychology, 90(2), 127-133. doi: http://dx.doi.org/10.1016/j.biopsycho.2012.02.022

Rowe, J. P., Shores, L. R., Mott, B. W., & Lester, J. C. (2010). Integrating learning and engagement in narrative-centered learning environments. Paper presented at the International Conference on Intelligent Tutoring Systems.

Roy, R., Bonnet, S., Charbonnier, S., & Campagne, A. (2012). Time-on-task effect on workload level discriminability through electroencephalography. Paper presented at the 18th International Conference on Biomagnetism (BIOMAG 2012).

Roy, R. N., Bonnet, S., Charbonnier, S., Jallon, P., & Campagne, A. (2015). A comparison of ERP spatial filtering methods for optimal mental workload estimation. Paper presented at the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).

Roy, S. N. (1953). On a heuristic method of test construction and its use in multivariate analysis. The Annals of Mathematical Statistics, 220-238.

Ryu, K., & Myung, R. (2005). Evaluation of mental workload with a combined measure based on physiological indices during a dual task of tracking and mental arithmetic. International Journal of Industrial Ergonomics, 35(11), 991-1009.

Sanders, A. F. (1979). Some remarks on mental load Mental workload (pp. 41-77): Springer.

Sanli, E. A., Patterson, J. T., Bray, S. R., & Lee, T. D. (2012). Understanding self-controlled motor learning protocols through the self-determination theory. Frontiers in psychology, 3.

Sarter, M., Gehring, W. J., & Kozak, R. (2006). More attention must be paid: the neurobiology of attentional effort. Brain research reviews, 51(2), 145-160.

Sassaroli, A., Zheng, F., Hirshfield, L. M., Girouard, A., Solovey, E. T., Jacob, R. J., & Fantini, S. (2008). Discrimination of mental workload levels in human subjects with functional near-infrared spectroscopy. Journal of Innovative Optical Health Sciences, 1(02), 227-237.

Sauseng, P., Griesmayr, B., Freunberger, R., & Klimesch, W. (2010). Control mechanisms in working memory: a possible function of EEG theta oscillations. Neuroscience & Biobehavioral Reviews, 34(7), 1015-1022.

Sauseng, P., Hoppe, J., Klimesch, W., Gerloff, C., & Hummel, F. C. (2007). Dissociation of sustained attention from central executive functions: local activity and interregional connectivity in the theta range. European journal of Neuroscience, 25(2), 587-593.

Sauseng, P., Klimesch, W., Schabus, M., & Doppelmayr, M. (2005). Fronto-parietal EEG coherence in theta and upper alpha reflect central executive functions of working memory. International Journal of Psychophysiology, 57(2), 97-103.

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. Psychological review, 82(4), 225.

Seidler, R. D., Bo, J., & Anguera, J. A. (2012). Neurocognitive contributions to motor skill learning: the role of working memory. Journal of motor behavior, 44(6), 445-453.

Shadmehr, R., & Wise, S. P. (2005). The computational neurobiology of reaching and pointing: a foundation for motor learning: MIT press.

Shaw, E. P., Rietschel, J. C., Hendershot, B. D., Pruziner, A. L., Miller, M. W., Hatfield, B. D., & Gentili, R. J. (In press). Measurement of attentional reserve and mental effort for cognitive workload assessment under various task demands during dual-task walking. . Biological psychology.

Shewokis, P. A., Ayaz, H., Panait, L., Liu, Y., Syed, M., Greenawald, L., . . . Lind, D. S. (2015). Brain-in-the-Loop learning using fNIR and simulated virtual reality surgical tasks: hemodynamic and behavioral effects. Paper presented at the International Conference on Augmented Cognition.

Shewokis, P. A., Shariff, F. U., Liu, Y., Ayaz, H., Castellanos, A., & Lind, D. S. (2017). Acquisition, retention and transfer of simulated laparoscopic tasks using fNIR and a contextual interference paradigm. The American Journal of Surgery, 213(2), 336-345.

Shuggi, I. M., Oh, H., Shewokis, P. A., & Gentili, R. J. (2017). Mental workload and motor performance dynamics during practice of reaching movements under various levels of task difficulty. Neuroscience, 360, 166-179.

Shuggi, I. M., Shewokis, P. A., Herrmann, J. W., & Gentili, R. J. (2017). Changes in motor performance and mental workload during practice of reaching movements: a team dynamics perspective. Experimental Brain Research, 1-19.

Silverman, S. (1985). Relationship of engagement and practice trials to student achievement. Journal of teaching in Physical Education, 5(1), 13-21.

Simon, H. A., & Chase, W. G. (1973). Skill in chess. American Scientist, 61, 394-403.

Slobounov, S. M., Ray, W., Johnson, B., Slobounov, E., & Newell, K. M. (2015). Modulation of cortical activity in 2D versus 3D virtual reality environments: an EEG study. International Journal of Psychophysiology, 95(3), 254-260.

Slobounov, S. M., Teel, E., & Newell, K. M. (2013). Modulation of cortical activity in response to visually induced postural perturbation: combined VR and EEG study. Neuroscience letters, 547, 6-9.

Smith, M. E., McEvoy, L. K., & Gevins, A. (1999). Neurophysiological indices of strategy development and skill acquisition. Cognitive Brain Research, 7(3), 389-404.

Springer, S. P., & Deutsch, G. (1998). Left brain, right brain: Perspectives from cognitive neuroscience: WH Freeman/Times Books/Henry Holt & Co.

Svensson, E., Angelborg-Thanderez, M., Sjöberg, L., & Olsson, S. (1997). Information complexity-mental workload and performance in combat aircraft. Ergonomics, 40(3), 362-380.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive science, 12(2), 257-285. doi: http://dx.doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2010). Element Interactivity and Intrinsic, Extraneous, and Germane Cognitive Load. Educational psychology review, 22(2), 123-138. doi: 10.1007/s10648-010-9128-5

Thayer, J. F., Åhs, F., Fredrikson, M., Sollers, J. J., & Wager, T. D. (2012). A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews, 36(2), 747-756.

Thayer, J. F., Hansen, A. L., Saus-Rose, E., & Johnsen, B. H. (2009). Heart rate variability, prefrontal neural function, and cognitive performance: the neurovisceral integration perspective on self-regulation, adaptation, and health. Annals of Behavioral Medicine, 37(2), 141-153.

Thong, T., Li, K., McNames, J., Aboy, M., & Goldstein, B. (2003). Accuracy of ultra-short heart rate variability measures. Paper presented at the Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE.

Tombini, M., Zappasodi, F., Zollo, L., Pellegrino, G., Cavallo, G., Tecchio, F., . . . Rossini, P. M. (2009). Brain activity preceding a 2D manual catching task. Neuroimage, 47(4), 1735-1746.

Van Merrienboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. Educational psychology review, 17(2), 147-177.

Vigneau, M., Beaucousin, V., Herve, P.-Y., Duffau, H., Crivello, F., Houde, O., . . . Tzourio-Mazoyer, N. (2006). Meta-analyzing left hemisphere language areas: phonology, semantics, and sentence processing. Neuroimage, 30(4), 1414-1432.

Ward, P., Hodges, N. J., Williams, A. M., & Starkes, J. L. (2004). Deliberate practice and expert performance Skill acquisition in sport: Research, theory and practice (pp. 231): Routledge.

Warm, J. S., Dember, W. N., & Hancock, P. A. (1996). Vigilance and workload in automated systems. In R. Parasuraman & M. Mouloua (Eds.), Automation and human performance: Theory and applications (pp. 183-200). Hillsdale, N.J.: Lawrence Erlbaum Associates.

Weber, E., & Doppelmayr, M. (2016). Kinesthetic motor imagery training modulates frontal midline theta during imagination of a dart throw. International Journal of Psychophysiology, 110, 137-145.

Weiss, M., & Chaumeton, N. (1992). Motivational orientations in sport. In T. S. Horn (Ed.), Advances in Sport Psychology (pp. 61-99). Champagne, IL: Human Kinetics.

Wickens, C. D. (2002). Multiple resources and performance prediction. Theoretical Issues in Ergonomics Science, 3(2), 159-177.

Wilson, G. F. (2002). An analysis of mental workload in pilots during flight using multiple psychophysiological measures. The International Journal of Aviation Psychology, 12(1), 3-18.

Wu, W. F., & Magill, R. A. (2011). Allowing learners to choose: self-controlled practice schedules for learning multiple movement patterns. Research quarterly for exercise and sport, 82(3), 449-457.

Wulf, G. (2007). Self-controlled practice enhances motor learning: implications for physiotherapy. Physiotherapy, 93(2), 96-101.

Wulf, G., Raupach, M., & Pfeiffer, F. (2005). Self-controlled observational practice enhances learning. Research quarterly for exercise and sport, 76(1), 107-111.

Wulf, G., & Toole, T. (1999). Physical assistance devices in complex motor skill learning: Benefits of a self-controlled practice schedule. Research quarterly for exercise and sport, 70(3), 265-272.

Yeo, G. B., & Neal, A. (2004). A multilevel analysis of effort, practice, and performance: effects; of ability, conscientiousness, and goal orientation. Journal of Applied Psychology, 89(2), 231.

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. Contemporary educational psychology, 25(1), 82-91.

Zusho, A., Pintrich, P. R., & Coppola, B. (2003). Skill and will: The role of motivation and cognition in the learning of college chemistry. International journal of science education, 25(9), 1081-1094.