Title	The role of neural efficiency, transient hypofrontality and neural proficiency in optimal performance in self-paced sports: A meta-analytic review
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Authors	[1]Edson Filho, Ph.D., [2]Urska Dobersek, Ph.D., [3]Tammy-Ann Husselman
Affiliations	[1]Wheelock College of Education & Human Development, Boston University; [2]Department of Psychology, University of Southern Indiana, Evansville, IN, USA; [3]School of Psychology, University of Central Lancashire, UK.
Corresponding Author	Edson Filho, Ph.D. Email: efilho@bu.edu
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Abstract

We examined changes in brain rhythms in relation to optimal performance in self-paced sports. Eight studies met the inclusion/exclusion criteria, representing 153 participants and eight different sports. We found that (a) optimal performance is characterised by increased alpha (g = .62, p = .02) and theta (g = .74, p = .002) across the cortex; (b) during optimal performance the frontal lobe is more relaxed (higher alpha; g = 1.06, p = .18) and less busy (lower theta; g = .38, p = .08), in comparison to the other brain lobes; (c) for the same given task, experts' brains are more relaxed (higher alpha, g = .89, p = .34) and less busy (lower theta, g = .91, p = .54) than novices' brains. Theoretically, our findings suggest that neural efficiency, neural proficiency, and transient hypofrontality are likely complementary neural mechanisms that underpin optimal performance. In practice, neurofeedback training should teach athletes how to amplify and suppress their alpha and theta activity across the brain during all movement stages.

Keywords: optimal performance; precision sports; EEG; meta-analysis

The role of neural efficiency, transient hypofrontality and neural proficiency in optimal performance in self-paced sports: A meta-analytic review

Introduction

Expert athletes perform consistently at optimal levels even under challenging conditions (Ericsson, 2007). Although the literature on optimal performance experiences is vast, sport psychologists do not agree on a general theory of optimal performance (Farrow & Baker, 2018). Influential frameworks, supported by psycho-physiological data, discussing optimal performance experiences include the individual zones of optimal functioning framework (Hanin, 2000), flow-feeling theory (Csikszentmihalyi & Jackson, 1999), multi-action plan model (Bortoli, Bertollo, Hanin, & Robazza, 2012; Robazza, Bertollo, Filho, Hanin, Bortoli, 2016), and the theory of reinvestment (Masters & Maxwell, 2008). While these frameworks diverge in their specific tenets, they converge in the overarching notions that (a) experts and novices function differently from a psycho-bio-social standpoint; and (b) the psycho-bio-social markers of optimal performance differ greatly from those of sub-optimal performance (Filho & Tenebaum, 2015; Ruiz, Raglin, & Hanin, 2017).

Sport psychologists subscribing to different theoretical frameworks have used the *expert-novice paradigm* to study optimal performance experiences (Filho & Tenenbaum, 2020). This experimental paradigm aims to capture the psycho-bio-social markers of optimal performance by comparing experts with novices (i.e., between-subjects) and/or by comparing experts' optimal and sub-optimal performance experiences (i.e., within-subjects). Thus far, most research based on the expert-novice paradigm has shown that, when performing at optimal level, experts exhibit more functional psycho-bio-social states than when performing poorly and in comparison to novices (Ericsson, 2007; Ruiz et al., 2017; Tenenbaum, Basevitch, Gershgoren, & Filho, 2013). Key characteristics of optimal performance include a focus on the present, physical and psychological relaxation (i.e., absence of somatic and cognitive anxiety), high levels of confidence, and effortless "automatic" movement (Williams & Krane, 2020). Relevant to the present study, these characteristics of optimal performance are thought to be underpinned by neural mechanisms (Holmes & Wright, 2017; Pacheco, 2016; Yarrow, Brown, & Krakauer, 2009).

Putative Neural Mechanisms Underpinning Optimal Performance Experiences

Scholars have explained optimal performance in light of the *neural efficiency hypothesis* (Del Percio et al., 2008; Haier et al., 1988; Holmes & Wright, 2017), which is also known as *psychomotor efficiency hypothesis* (see Hatfield, Jaquess, Lo, & Oh, 2020). According to this hypothesis, experts perform better than novices because their brains work smartly by only recruiting the spatiotemporal areas needed to perform the task at hand (Grabner, Neubauer, & Stern, 2006). Additionally, research in sports has attributed optimal performance and expert-novice differences to neural efficiency. Sport psychologists have suggested that it is because of a state of neural efficiency that performers report being in a state of automaticity when "in the zone", "in flow" or showing a "type-1" performance (Bertollo, Doppelmayr, & Robazza, 2020; Filho & Tenenbaum, 2015). Over years of deliberate practice, experts learn to recruit only the neural networks needed to optimally perform a given task (Ericsson, 2007). Conversely, when performing poorly (e.g., choking under pressure), skilled performers reinvest mental resources in unnecessary elements of their performance (Masters & Maxwell, 2008), and thus do not exhibit a state of neural efficiency.

Another explanation for optimal performance experiences can be found in the *transient hypofrontality hypothesis* proposed by Dietrich (2003, 2006). According to this hypothesis, decreased functional activity (e.g., neurochemical and blood flow) in the frontal lobe, rather than in the whole brain, explains optimal performance experiences. In particular, Dietrich (2003, 2006) argues that optimal performance is an altered state of consciousness that is only possible due to the temporary shutdown of conscious and deliberate thinking (i.e., type-2 performance), as manifested by a temporary frontal hypofunction. In this regard, it has been long established that the frontal lobe, which was the last part of the brain to evolve, exerts a supervisory role over higher order executive functions, such as attentional control and self-appraisal (Coolidge & Wynn, 2001). The transient hypofrontality hypothesis resonates with the aforementioned frameworks of performance because athletes performing at optimal levels do not reinvest their attention on the task. Rather, they report being in a state of altered consciousness (e.g., in the zone, in flow, or type-1 performance) which is associated with automaticity and time distortion. Notably, this state of hypofrontality is thought to be "transient" because optimal performance experiences are relatively rare and brief, and chronic hypofrontality is associated with neurodegenerative conditions, such as dementia (Dietrich, 2003, 2006).

Noteworthy, the notion that reduced brain activity, whether in the frontal lobe or across the whole brain, explains optimal performance experiences has been questioned in sports and other domains of human performance (Dunst et al., 2014; Vickers & Williams, 2017). In this regard, Neubraeur and Fink (2009) conducted a review of the literature and concluded that a state of neural efficiency only explains optimal performance in tasks of easy or moderate complexity. For difficult tasks, they observed that individuals needed to recruit more cortical resources to perform at optimal level. Moreover, recent empirical studies revealed that increased theta activity in the frontal lobe, a marker of "brain busy-ness" (see Pacheco, 2016), underpins optimal performance experiences in both motor and cognitive tasks (Di Fronso et al., 2016; Katahira et al., 2018). In light of this emerging evidence, scholars have recently proposed the *neural proficiency hypothesis* (Bertollo et al., 2016; 2020).

According to the neural proficiency hypothesis, athletes need to engage in both efficient (system-1; fluid and automatic thinking) and effortful (system-2; deliberative thinking) processing to be able to consistently perform at optimal levels (Bertollo et al., 2016; Bertollo et al., 2020). Previous research suggests that in order to optimally perform complex tasks under high-pressure situations athletes must be able to (a) purposefully recruit neural networks that allow them to perceive the environment, make decisions, and regulate their thoughts, feelings and behaviors (Filho & Tenebaum, 2015; Tenenbaum et al., 2013); and (b) silence the parts of their brains that are not relevant to the task at hand (i.e., "quiescense state"; see Hatfield et al., 2017). In other words, proficient athletes can adeptly use and switch between these two types of processing during competition. To shed further light on this notion of neural proficiency, as well as the concepts of neural efficiency and transient hypo-frontality, we conducted a meta-analytic review grounded on the expert-novice paradigm in an effort to systematize and benchmark literature used to inform neurofeedback interventions aimed at enhancing the probability of optimal performance experiences in sports.

The Present Study

Given that the neural efficiency hypothesis, the transient hypofrontality hypothesis, and the neural proficiency hypothesis have been used to explain optimal performance experiences in sports, we sought to examine which of these hypotheses better explains optimal performance in self-paced precision sports. Specifically, we adhered to the PRISMA guidelines for meta-analytical reviews (see http://prisma-statement.org/) and purposefully focused our search on self-paced sports studied through electroencephalogram (EEG) power frequency spectrum analysis for three reasons. First, self-paced sports (e.g., archery, shooting) are significantly less impacted by movement artefacts than externally-paced sports (e.g., football, volleyball), and can be reliably monitored using EEG methods to allow insights on the pre-movement (e.g., perception, response selection), the execution (i.e., during movement), and the post-movement phases (e.g., action execution; see Bertollo et al., 2020; Filho & Tenenbaum, 2020). Second, EEG is one of the most commonly used brain-imaging methods in sports because of its portability and high ecological validity (Holmes & Wright, 2017; Yarrow et al., 2009). Third, EEG power frequency spectrum analysis is very relevant to inform applied neurofeedback interventions aiming to increase the probability of optimal performance experiences (Pacheco, 2016; Strack, Linden, & Wilson, 2011; Xiang, Hou, Liao, Liao, & Hu, 2018). To this extent, there is consensus that optimal performance experiences in sports are a multidimensional phenomenon indexed in the brain by different brain rhythms, particularly alpha (relaxation), beta (sensory motor integration) and theta (focused attention) waves (Cheron et al., 2016; Pacheco, 2016). Simply stated, by looking at the patterns of these three different brain rhythms across brain regions (i.e., frontal, central, temporal, parietal, occipital), we sought to understand whether neural efficiency, transient hypofrontality, and neural proficiency underpin optimal performance experiences in self-paced precision sports.

Methods

Search Strategy

A total of eight databases (i.e., ProQuest Central, ProQuest Psychology Journals, PsycARTICLES, PsycINFO, SPORTDiscus, MEDLINE, Scopus, and Web of Science) were searched using keywords (i.e., *EEG* AND *sports* AND *performance*) for primary peer-reviewed research that examined changes in brain power in self-paced precision sports. The search strategy also included snowball procedure by examining reference lists from previous reviews and research papers. The search included all papers published up to January 1st, 2021. The first and last authors independently conducted the searches. Titles and abstracts of potentially relevant articles were identified and screened by the first and last authors to determine whether they examined performance involving self-paced tasks and any methods related to EEG. Duplicate articles were excluded during the search and full-texts of potentially relevant articles were obtained and independently assessed by the first and the second authors. After this assessment, the first and second authors met to arrive at a consensus on the inclusion/exclusion criteria for each paper. Disputes were adjudicated by discussion until consensus was reached for all included articles.

Study Inclusion Criteria. We sought to identify primary studies that examined EEG power and performance during self-paced sports (e.g., pistol shooting, archery, golf putting). Studies were included if they (1) were written in the English language; (2) used a quantitative design and provided sufficient information to allow for the computation of effect sizes (ESs; e.g., means, *SD*s, sample sizes, *F*-values); and (3) examined EEG power and self-paced precision sports involving comparisons between experts and novices or between optimal and sub-optimal performances. There were no geographical, cultural, or time-period (in which studies were published) restrictions.

Study Exclusion Criteria. Studies were excluded if they (1) were written in a non-English language; (2) were reviews, qualitative or case studies, or retracted studies; (3) did not examine EEG power frequency spectrum analysis, e.g., coherence, event-related potential, event synchronization/desynchronization analysis; (4) examined open skills sports (e.g., ice hocking, baseball batting) and were based on a learning paradigm (i.e., test, acquisition, post-test, retention, and transfer stages; see Wang & Chen, 2014) as opposed to a performance paradigm; (5) did not provide enough information to calculate the ESs. Table 1 provides the detailed description of inclusion/exclusion criteria according to a Population, Exposure/Intervention/Comparison, Outcomes, and Study Design (PE/I/COS; see Brown et al., 2006).

Coding Procedures

Data Extraction. Data extraction was performed independently by all three authors. The information extracted included the participants' characteristics (e.g., number of participants, gender, age, sport, expertise level, handedness) and the studies' characteristics (e.g., design, independent and dependent variables, type of statistical analysis, sampling rate in Hz, number of EEG channels, impedance, whether the authors removed artifacts (Yes/No), relevant data to calculate ESs, and the main findings). The authors had full access to the paper details during the coding process and were not blinded to one another. The extraction tables were examined for accuracy and completeness by all three authors. Information for the selected studies is presented in Table 2.

--------------------Include Table 2 here------------------------

Methodologic Rigor: Quality Assessment. Quality assessments in meta-analysis is based on the critical evaluation of multiple factors within and between the included studies. Raters' judgments must be independent and constrained via a standardized protocol to reduce the potential for biases in the assessment process. Therefore, each study included in our meta-analysis was assessed for quality via quantitative analysis by two investigators who have expertise in the field of sport psychology and measurement and statistics (first and second author), and neuroscience (first author). To assess the quality of studies, we adopted a previously developed scale (see Zach, Dobersek, Filho, Inglis, & Tenenbaum, 2018), which was used in a meta-analysis in sport psychology and developed based on the guidelines for reporting research in psychology by the American Psychological Association Publications and Communications Board task force (Appelbaum et al., 2018). Specifically, we used a 7-item quality scale addressing the following dimensions: (1) statement of purpose and hypotheses, (2) target population, (3) description of the EEG and outcome measures, (4) design, (5) statistical analyses, (6) adequacy of results, and (7) overall quality of the study. Each item was anchored on a 10-point Likert-type scale ranging from 1 (*not acceptable*) to 10 (*excellent*). The inter-rater agreement was 97%.

Dependent Variables

Based on the information presented in the included articles, we coded the following independent variables: (1) alpha power: 8-12 Hz; (2) beta power: 13-30 Hz; and (3) theta power: 4-8 Hz. As discussed above, these brain rhythms are at the core of peak performance experiences in self-paced sports (Bertollo et al., 2020; Hatfield et al., 2020; Holmes & Wright, 2017; Vickers & Williams, 2017).

Moderator Variables

We included the main type of analysis, time of assessment, and hypofrontality as moderator variables.

Main Type of Analysis. As the expert-novice paradigm is implemented through both between- and within-subjects designs (Filho & Tenenbaum, 2020), we were interested in whether the main type of analysis moderated the linkage between brain power and performance. We coded the main analysis as between-subjects (0) and within-subjects (1). The ESs that reflected the data between experts and novices were coded as between-subjects analysis, and the ESs that reflected the data between experts' optimal and sub-optimal performance were coded as within-subjects analysis.

Time of Assessment. We were also interested in whether time of assessment had an impact on the relationship between EEG and performance. We coded time assessment when studies presented the data on EEG before performance (1) and across performance (0).

Hypofrontality. Congruent with the transient hypofrontality hypothesis (Dietrich, 2003, 2006), we compared EEG activities in the frontal lobe and the other the brain regions (i.e., central, temporal, parietal, and occipital) in relation to performance.

Statistical Methods

The statistical techniques used to compute the estimates of the ESs were adopted from Borenstein and colleagues (Borenstein, Hedges, Higgins, & Rothstein, 2011; Borenstein, Rothstein, & Cohen, 2005). We calculated the *d* family ESs or standardized mean difference either between the novices and experts (i.e., between-subjects analysis) or between participants' optimal/best or sub-optimal/worst performances (i.e., within-subjects analysis) divided by the pool standard deviation (*SD*) for all studies. When the means and *SD*s were not available, we used *F*-values and *df* to calculate the ESs or transformed *partial eta squared* ESs into *d* family ESs. Because most of the studies presented more than one ES per brain region (e.g., Fz, F3, F4; P3, P4, Pz), we averaged the ESs that represented the same region within a given study to allow for statistical independence in the data set. This procedure eliminates ES biases, which are inherent in single studies with multiple ESs (Lipsey & Wilson, 2001). Additionally, given that Cohen's *d* tends to overestimate the effects in smaller samples and most of the studies included in our meta-analysis had fewer than 20 participants, we used Hedge's *g* ESs (Hedges, 1981, 1989; Hedges & Olkin, 1985). All ESs were calculated using the Campbell's Collaboration calculator (www.campbellcollaboration.org/resources) and were interpreted according to Cohen (Cohen, 1988), with an ES of .20 indicating a small effect, .50 a medium effect, and > .80 a large effect.

Furthermore, we calculated confidence intervals and performed a test of heterogeneity of distribution. In addition to Cochran's Q statistic, we reported the I^2 statistics because Q has a small power as a comprehensive test of heterogeneity especially when the number of studies in a meta-analysis is small (Gavaghan, Moore, & McQuay, 2000). Additionally, the Q test does not inform us about the extent of true heterogeneity among the studies, but only about its significance, whereas the I^2 statistic indicates which proportion of the observed variance reflects differences in true ESs rather than sampling error (Higgins & Thompson, 2002; Higgins, Thompson, Deeks, & Altman, 2003; Huedo-Medina, Sánchez-Meca, Marín-Martínez, & Botella, 2006). To identify potential outliers and to provide a graphical overview of the ESs for each study, we constructed funnel and forest plots. All calculations were performed using the Comprehensive Meta-Analysis program Version 3.0 (Borenstein et al., 2005).

Results

Description of Studies

Our initial search without the duplicates resulted in 267 potentially relevant articles that were screened according with the inclusion/exclusion criteria. Most studies were excluded because they examined irrelevant topics (n = 174) or were literature reviews or case studies (n = 37). This screening resulted in 55 articles which were then critically evaluated. Additional studies were excluded because of the irrelevant outcome (n = 40) or because they did not present enough data to calculate the ESs (n = 7). This analysis resulted in eight papers, published between 1990 and 2016, that met our inclusion/exclusion criteria. As per Preferred Reporting Items for Systematic Review and Meta-Analysis statement (PRISMA; see Moher et al., 2009), results from each stage of meta-analysis are presented in Figure 1.

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The total sample included 153 right-handed participants (90 males, 38 females). The sample size across studies ranged from 6 to 34 participants, with 54 novices and 93 experts performing archery, shooting, golf putting, free throwing, or dart throwing. On average, the participants were 26.38 years old (SD = 2.33; range: 18-38 years of age) and reported playing experience ranging from 0 to 15.9 years (M = 10.48; SD = 5.19).

The overall quality of studies was moderately good ($Q_{quality}$ = 7.51, SD = 0.46), as measured by our self-developed scale. Tables 2 and 3 provide the Hedge's g ESs and their associated 95% CI, forest plots, and Q heterogeneity statistics for the studies included in the analyses for the alpha and theta frequency ranges, respectively. We were unable to compute forest and funnel plots for the beta band given that only two studies (Cheng et al., 2015; Salazar et al., 1990) included results for beta activity.

The test of heterogeneity for alpha (Q = 24.31, df = 7, $p < 0.05$, I^2 = 71.20%), beta (Q = 39.56, df = 1, $p < 0.05$, I^2 = 97.47%) , and theta power (Q = 11.17, df = 5, $p < 0.05$, I^2 =

55.25%) suggested that the true effect size is identical in all studies and that approximately 75% of the variance in the observed effects is a true effect rather than sampling error ($I^2_{average}$ = 74.64%). The 95% prediction interval was -0.91 to 2.15 and -0.65 to 2.13 for alpha and theta, respectively. Given that the ESs vary considerably because of between-study differences (e.g., study procedures, types of sport, years of sport experiences, participants' age) and we want to generalize our meta-analytic findings beyond the current sample of studies, we adopted a random-effects model (see Borenstein, Hedges, Higgins, & Rothstein, 2011; Borenstein, Rothstein, & Cohen, 2005).

The funnel plots for alpha and theta waves (see Figure 2) are based on the Hedge's *g* ES (x-axis) and standard errors (y-axis). Dots represent each individual study. Given that both funnel plots are slightly asymmetrical, we further examined the possibility of publication bias. The Egger test of intercept was not significant for both the alpha (t = 1.46, p = .33) and the theta (t = 1.16, p = .16) frequency bands, and Owrin's Fail-safe *N* revealed that 40 and 36 additional studies would be needed to bring the observed ESs to a trivial value of Hedge's g = .10 for alpha and theta, respectively. Thus, publication bias was not a concern in our study and the observed spread of ESs in the funnel plot likely reflects the fact that we averaged ESs across brain lobes, and that alpha and theta waves behave differently (amplified or suppressed) across the cortex during motor performance (Yarrow et al., 2009).

----------Include Figure 2 here----------------------

Overall, the analyses of the ESs suggested that optimal performance was characterized by higher alpha and theta power, in comparison to sub-optimal performance. Specifically, the analysis of the eight ESs for the alpha band suggested a medium significant effect (g = .62, p = .02, $CI_{95\%}$ = 0.10, 1.15), and the analysis of the six ESs for the theta band suggested a medium significant effect (g = .74, p = .002, $CI_{95\%}$ = 0.26, 1.21). The analysis of the two ESs for the beta band revealed a large non-significant effect (g = 5.16, p = .28, $CI_{95\%}$ = -4.20, 14.51).

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Moderator Analyses

Three moderators (i.e., main type of analysis, time of assessment, and hypofrontality) were examined for the alpha and theta frequencies. Again, only two studies (Cheng et al., 2015; Salazar et al., 1990) measured beta activity, and thus we were unable to conduct moderator analysis for this frequency range. Because we assumed that ESs differ from study to study, we employed a more conservative random-effects model for all analyses.

Main Analysis Type

Alpha power was higher for between-subject analysis (g = .89) than for studies employing a within-subjects analysis (g = .35), Q = 0.95, df = 1, p = .34. Conversely, theta power was lower for the between-subjects analysis (g = .60) than for the studies employing a within-subjects analysis (g = .91), Q = 0.37, df = 1, p = .54. Thus, albeit non-significant, the difference *within* experts' optimal and sub-optimal performance is less pronounced than the difference *between* the brain activity of experts and novices.

Time of Assessment

Alpha power was higher (g = 1.22) for the studies measuring brain activity across movement time (i.e., before, during, after), compared to studies measuring brain activity before movement initiation (g = .45), Q = 1.53, df = 1, p = .22. Similarly, theta power was higher (g = 1.13) for the studies measuring brain activity across performance time (i.e., before, during, after), compared to the studies measuring brain activity before movement initiation (g = .58), Q = 1.06, df = 1, p = .30. This pattern of results suggests that the time of assessment did not influence the magnitude of alpha and theta activity in the performance of self-paced sports.

Hypofrontality

Alpha power was higher in the frontal lobe (g = 1.06) than in the other brain lobes (g = .36), Q = 1.79, df = 1, p = .18. Conversely, theta power was lower in the frontal lobe (g = .38) than in the other brain lobes (g = 1.08), Q = 3.01, df = 1, p = .08. Albeit non-significant, this pattern of results suggests that increased alpha and reduced theta activity in the frontal lobe might be implicated in optimal performance experiences, as discussed in detail next.

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Discussion

Based on the expert-novice paradigm, we conducted a meta-analysis of experimental papers measuring changes in brain power between experts and novices, or between experts' optimal and sub-optimal performances in self-paced sports. We sought to understand whether neural efficiency, transient hypofrontality, or neural proficiency underpinned optimal performance experiences (e.g., in the zone, in flow, or type-1 performance) in self-paced sports, as previously suggested in narrative reviews in sport psychology (Bertollo et al., 2020; Hatfield et al., 2020; Holmes & Wright, 2017; Vickers & Williams, 2017). To this end, we examined changes in alpha, beta, and theta activity as these brain rhythms have been previously linked to optimal performance experiences in self-paced sports. We found a complex pattern of results that must be interpreted together rather than in parts, as is often the case in psychophysiological research (Cacioppo, Tassinary, & Berntson, 2007). In a nutshell, we propose that neural efficiency, transient hypofrontality, and neural proficiency are all implicated in optimal performance in self-paced sports, as elaborated below.

The Role of Brain Proficiency in Optimal Performance Experiences

Our main analysis revealed that beta waves did not differentiate experts from novices, or best from worst performances. However, this analysis was based on (only) two ESs, thus suggesting that scholars in sport psychology either have not examined this brain rhythm as much as alpha and theta waves or that they have not reported non-significant findings for this frequency range. Therefore, further research is warranted to clarify the role of beta waves on optimal performance experiences, especially given that this brain rhythm has been related to sensorimotor integration (Cheron et al., 2016).

Furthermore, our main analysis revealed that optimal performance is characterized by an increase of moderate magnitude in both the alpha and theta brain rhythms. These findings echo previous research suggesting that “a relaxed and focused” brain is essential for optimal performance in sports (Bertollo et al., 2020; Hatfield et al., 2020; Pacheco, 2016). Specifically, the neural marker of a “relaxed brain” involves increased alpha activity across the cortex, as an increase in this brain rhythm indicates the inhibition of brain areas unrelated to the task at hand (Cheron et al., 2016; Di Fronso et al., 2016). In turn, an increase in theta activity indicates a “focused brain” as an increase in this brain rhythm signals engagement of the working memory and motor control (Katahira et al., 2018; Pacheco, 2016).

Our analysis of the time of assessment moderator showed that the increased alpha and theta activity accompany optimal performance experiences did not differ across time windows (i.e., before, during, and after movement execution). Thus, when performing at optimal levels, athletes remain relaxed and focused for the planning (pre-movement), execution (during movement), and feedback (post-movement) stages of movement action. As such, behavioral and neurofeedback interventions aimed at enhancing athletes’ ability to reach and sustain optimal performance should target the pre-, during, and post-movement stages, and future research should continue to study brain activity related to all of these stages.

Taken together, these findings support the neural proficiency hypothesis (Bertollo et al., 2016; 2020). Notably, given that we averaged ESs across brain lobes, the spread of ESs in the funnel plot corroborates the overarching notion that different brain waves behave differently (amplified or suppressed) in the different areas of the brain during optimal performance, a finding consistent with the brain proficiency hypothesis. Importantly, the large negative ESs reported by Salazar et al. (1990) in the temporal lobe likely signals a functional suppression of a stepwise (inner speech) serial process during motor performance, whereas the general trend of increased alpha activity across the cortex signals a global state of relaxation ("cortex idling"; see Hatfield et al., 2020; Bazanova & Vernon, 2014), both markers of optimal performance experiences in sports (Di Fronso et al., 2016; Yarrow et al., 2009). Therefore, to perform at optimal levels some neural networks must be "tuned down" (i.e., quiescence state), whereas others must be "tuned up" (i.e., neural recruitment). Accordingly, neurofeedback protocols should be geared towards teaching athletes how to simultaneously activate (e.g., attentional focus regulation targeting theta waves) and silence (e.g., alpha peak neurofeedback) different areas of their brains. Learning how to silence the frontal lobe seems to be particularly important for athletes in self-paced sports, as elaborated upon next.

The Role of Transient Hypofrontality in Optimal Performance Experiences

Our analysis of the hypofrontality moderator lends partial support to the transient hypofrontality hypothesis. Specifically, we found a non-significant increase in alpha activity in the frontal lobe, and a non-significant decrease in beta activity in the frontal lobe, in comparison to all other brain lobes (i.e., central, temporal, parietal, and occipital). Although non-significant, this pattern of results, which was based on a small number of ESs, suggests that transient hypofrontality might be implicated in optimal performance experiences in self-paced sports. Thus, the notions of neural proficiency and transient hypofrontality might not be at odds with one another. In theory, athletes need to engage and disengage different areas of their brains to perform at optimal levels (i.e., brain proficiency); however, their frontal lobe is working at the lowest rate possible (i.e., transient hypofrontality) and that is likely why athletes' report feelings of automaticity, control, confidence, and relaxation when performing at optimal levels (Csikszentmihalyi & Jackson, 1999; Williams & Krane, 2020).

The observed non-significant increase in alpha and decrease in theta activity in the frontal lobe, in comparison to all other lobes, might be related to the fact that athletes performing at optimal levels experience an altered state of consciousness (e.g., in the zone, in flow, or type-1 performance) due to transient hypofrontality, as proposed by Dietrich (2003, 2006). First, reduced alpha activity in the frontal lobe, in comparison to all other lobes, is a biomarker of relaxation and confidence (as opposed to somatic and cognitive anxiety), which in turn are characteristics of optimal performance experiences in sports (Pacheco, 2016; Williams & Krane, 2020). Second, an increase in theta activity across the whole brain, coupled with a relative (with respect to the other brain lobes) theta decrease in the frontal lobe, likely signal that athletes are "focused but not too focused" while performing at optimal levels, as theta activity in the frontal lobe is a marker of "brain busy-ness" (Pacheco, 2016). To perform at optimal levels athletes must be focused, as they monitor core elements of action and environmental cues, make decisions, and block distraction (Bortoli et al., 2012; Filho & Tenebaum, 2015; Tenenbaum et al., 2013). However, athletes cannot be too focused by overly monitoring themselves, the task, and the environment, or they will regress to a step-by-step modus operandi that leads to choking rather than optimal performance and is associated with novice rather than expert functioning in sports (Bortoli et al., 2012; Masters & Maxwell, 2008). To this last point, we also analysed differences between expert and novices (between-subjects design), and optimal and sub-optimal experiences of experts (within-subjects design), as discussed next.

The Role of Neural Efficiency in Optimal Performance Experiences

We found a non-significant effect for the studies' "main types of analysis moderator". Specifically, we found a non-significant increase in alpha and non-significant decrease in theta activity for between-subject studies, in respect to within-subject designs. Theoretically, although non-significant, this pattern of results is congruent with the neural efficiency hypothesis (Del Percio et al., 2008; Dunst et al., 2014; Grabner et al., 2006). Methodologically, this finding suggests that both within- and between-subjects can be used to study the neural markers of skilled performance. Nevertheless, we suggest that more within-subject studies with experts should be conducted so that we can not only understand *what* the differences between experts and novices are, but also *how* experts have learned to control their mental states in order to consistently perform at optimal levels (see Ericsson, 2007; 2020). From an applied standpoint, we reason that long-term neurofeedback protocols with expert individuals are important. We suggest these should include assessment of the performers' overall neural efficiency for a given task (see also *net efficiency*; Hatfield et al., 2020), as a form to monitor mental fatigue over the course of a competitive season. Studies on the neural markers of mental fatigue is also a ripe area for future research (Pageaux & Lepers, 2018). Additional areas for future research, and the limitations and strengths of the present study are discussed next.

Limitations, Strengths and Future Research

This paper is not without limitations. First, as is the case with meta-analytical work, there is a chance that we might have missed relevant papers. However, as our analysis revealed, at least 36 new papers meeting our inclusion/exclusion criteria would be needed to bring the differences reported here to a trivial effect for a criterion of Hedge's g = .10. Previous comprehensive narrative reviews of the field have not cited an excess of 36 papers reporting changes in brain power in relation to performance in self-paced sports (Bertollo et al., 2020; Hatfield et al., 2020; Holmes & Wright, 2017).

Second, we were unable to examine the moderating role of different types of self-paced sports on the linkage between brain rhythms and performance. We ended-up with a mixed-bag of self-paced sports (i.e., archery, basketball free throwing, golf putting, pistol shooting, and rifle-shooting) that could not be meaningfully (from a motor control and statistical standpoint) compared. Accordingly, where possible, future meta-analytical reviews should examine the moderating role of sport type and its relation between brain rhythms and performance to allow for the development of sport-specific interventions.

Third, our study was narrow in focus, which is both a weakness and a strength. We only examined experimental studies measuring changes in brain power between experts and novices, or optimal and sub-optimal performance experiences, in self-paced sports. Noteworthy, we set a stringent inclusion criterion because of the recent boom of brain imaging papers in sports, several of which are not experimental nor target optimal performance experiences (Holmes & Wright, 2017). We reasoned that only stringent inclusion criteria would allow for an in-depth analysis of research relevant to the development of neurofeedback interventions for performance optimization in sports. Although previous narrative reviews covering different EEG methods of analysis and other brain imaging techniques might have achieved greater breadth of knowledge, they did not quantify the impact of brain rhythms on optimal performance in self-paced sports, as we have done here. To this extent, future meta-analyses of externally-paced sports are warranted, especially given that mobile EEG systems have been increasingly used to study dynamic sport settings (e.g., Christie, Di Fronso, Bertollo, & Werthner, 2017; Ladouce, Donaldson, Dudchenko, & Ietswaart, 2017). A future meta-analytical work examining studies on brain coherence in both self-paced and externally-paced sports is warranted given that coherence neurofeedback is also relevant for performance optimization in sports (Pacheco, 2016; Strack et al., 2011; Xiang et al., 2018).

Fourth, due to the available data, we averaged ESs across brain lobes and were unable to examine hemispherical differences and compare all lobes with one another. Thus, per current standards of reporting (Appelbaum et al., 2018), we urge authors to provide complete statistical reports including significant and non-significant findings for all variables of interest (e.g., all brain waves and sites studied). Such complete reports will allow future meta-analyses in sports to examine potential differences across hemispheres and reach enough power for multi-comparison among the various brain lobes.

Conclusions

Our findings advance the literature by revealing the role of alpha and theta activity in optimal performance, with respect to the theoretical notions of neural efficiency, transient hypofrontality and neural proficiency. Previous narrative reviews have speculated that neural efficiency, transient hypofrontality, and neural proficiency were important to optimal performance (Bertollo et al., 2020; Hatfield et al., 2020), and even at odds with one another (Vickers & Williams, 2017). However, our analyses revealed that these neural mechanisms might be complementary to each other and underpin optimal performance experiences in self-paced sports. Specifically, we observed that (a) a relaxed (increased alpha activity) and focused (increased theta activity) brain is needed for optimal performance, and thus both the activation and the down-regulation of brain areas is needed for optimal performance (i.e., *neural proficiency*); (b) the frontal lobe is likely working at the highest alpha (relaxation) and lowest theta (attentional control) activity possible (i.e., *transient hypofrontality*) and that is likely why athletes report running in automatic and feeling complete focus and immersion on the task at hand when experiencing optimal performance; and (c) for the same given task experts show non-significant higher levels of relaxation (increased alpha) and lower levels of attentional control (reduced theta waves) across the cortex, in comparison to novices (i.e., *neural efficiency*). Finally, we learned that athletes' brains must be relaxed and focused but not too focused (i.e., an increase in alpha and theta activity across the cortex) across all stages of movement action, namely the planning (pre-movement), execution (during movement), and feedback stages (post-movement). Given these findings, neurofeedback protocols should teach athletes how to control (increase and decrease) their alpha and theta activity across the whole brain and across movement stages (the pre, during and post), and particularly in the frontal lobe.

Table 1

Detailed description of inclusion/exclusion criteria according to the Population, Exposure/Intervention/Comparison, Outcomes, and Study Design (PE/I/COS) Framework

Search Strategy	Details
Inclusion criteria	P: Adults and adolescents E/I/C: Self-paced precision sports involving comparison between experts and novices or between optimal and sub-optimal performances O: EEG power frequency spectrum analysis S: Observational studies (e.g., cross-sectional studies, longitudinal studies, case control), non-/randomized control trials
Exclusion criteria	P: N/A E/I/C: Studies on open skills sports and based on learning paradigm O: Studies that did not include EEG power frequency spectrum analysis (e.g., coherence, event-related potential, even synchronization analysis) S: Qualitative studies, reviews, letters, book chapters, articles without quantitative data, retractions
Language	English
Time filter	None
Database	ProQuest Central, ProQuest Psychology Journals, PsycARTICLES, PsycINFO, SPORTDiscus, MEDLINE, Scopus, Web of Science

Table 2

Summary Table

Author	Participants*	Sport	Age	Years of experience	Sampling rate	Channels	Design	Artifact removal	Impedance	Overall results
Baumeister et al. (2008)	Skilled males = 9 Novice males = 9	Golf putting	Experienced (*M* = 26.4, *SD* = 4.1); Novices (*M* = 24.6, *SD* = 3.4)	7.6 years (*SD* = 4.2) Novices: no experience	512Hz	10-20 system (Fz, F3, F4, Cz, C3, C4, Pz, P3, P4, T3, T4, T5, T6, Cz as a reference) (14 electrodes)	Between: Expert vs. novice paradigm	Yes	20MΩ	Experts showed higher theta and alpha power in comparison with novices.
Bertollo et al. (2016)	Elite experts Males = 6 Females = 4	Pistol Shooting	18-29 (*M* = 22.8, *SD* = 3.5)	14.5 years (*SD* = 4)	1024Hz	10-20 system (32 electrodes)	Mixed: 4 types of performance	Yes	10KΩ	Higher alpha and theta power were observed for better performance.
Cheng et al. (2015)	Experts = 14 Novices = 11	Dart-throwing	Experts (*M* = 41.86, *SD* = 13.79) Novices (*M* =22.04, *SD* = 2.09)	13.93 years (*SD* =10.02)	500Hz	10-20 system (Fz, F3, F4, C3, C4, T3, T4, Pz, P3, P4, O1, O2) (12 electrodes)	Between: Expert vs. novice paradigm	Yes	10KΩ	Experts showed higher power for alpha and beta power; no difference in power for theta power compared to novices.
Chuang et al. (2013)	Experienced males = 15	Basketball free throw	*M* = 21.74, *SD* = 1.63	6.95 years (*SD* = 2.53)	NR	10-20 system; F3, F4, Fz, P3, P4, Pz, Cz, Fpz, A1, A2 (10 electrodes)	Within: successful vs. unsuccessful performance	Yes	5KΩ	Higher theta power was observed for better performance.
Crews et al. (1993)	Males = 17 Females = 17 50% = amateurs, 50% = professionals	Golf putting	M = 29.5, M_{males} = 31.0, $M_{females}$ = 28.0	M = 15.9, M_{males} = 16.06, $M_{females}$ = 15.8	250Hz	Biolab System; 10-20 system (T3, T4, C3, C4) (4 electrodes)	Mixed: 40 putts	Yes	5KΩ	Increased alpha power was observed for better performance.

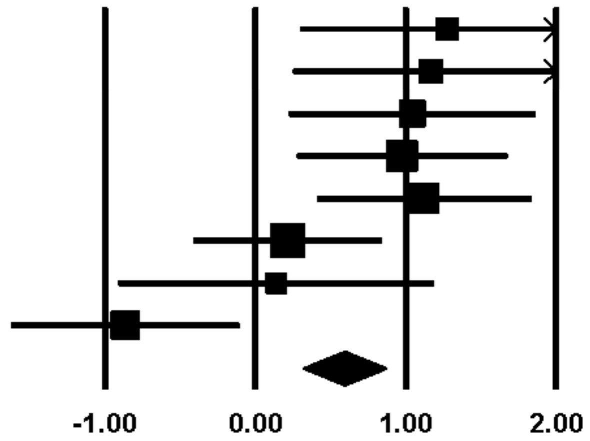
Hunt et al. (2013)	Males = 15 Females = 2	Shooting	18-38 (*M* = 22.17, *SD* = 4.79)	No competitive shooting experience	1000Hz	10-20 system F3, F4, C3, C4, P3, P4, T3, T4, O1, O2 (10 electrodes)	Between: Winning vs. losing group	Yes	10KΩ	The winning group showed less alpha and theta power than the losing group.
Loze et al. (2001)	Males = 6	Air-pistol shooting	*M* = 36.4, *SD* = 2.4	4 years international experience	140Hz	10-20 system (Oz, T3, T4) (3 electrodes)	Within: Best vs. worst shots	Yes	5KΩ	Higher alpha power was observed for better performance.
Salazar et al. (1990)	Males = 13 Females = 15	Archery	13-36 (*M* = 21)	National archery team	250Hz	10-20 system (T3 - left temporal; T4 - right temporal) (2 electrodes)	Within: Best vs. worst shots	Yes	NR	Greater alpha and beta power were observed for better performance.

*All participants were right-handed.
Note: *M* = mean, *SD* = standard deviation, NR = not reported; F = Frontal lobe; C = Central lobe; T = Temporal lobe; P = Parietal lobe; O = Occipital lobe.

Table 3

Cohen's *d*, Hedge's *g*, 95% Confidence Intervals, *Q* Statistics, and forest plot for the studies included in the analysis for Alpha Power (8-13Hz).

Study	Effect Size (*d*) per ROI WB	F	C	T	P	O	Overall ES (*g*)	95% *CI*	Hedge's *g* [95% *CI*]	*Q*
Baumeister et al. (2008)					1.34		1.28	[0.30, 2.25]		
Bertollo et al. (2016)		1.22			1.22		1.17	[0.25, 2.08]		
Cheng et al. (2015)		1.69	1.19		1.20	.23	1.04	[0.23, 1.86]		
Chuang et al. (2015)		1.00					0.98	[0.28, 1.67]		
Crews & Landers (1993)	1.15						1.12	[0.41, 1.83]		
Hunt et al. (2013)	.22						0.22	[-0.41, 0.84]		
Loze et al. (2010)				.14		.16	0.14	[-0.91, 1.18]		
Salazar et al. (1990)				-.89			-0.86	[-1.62, -0.11]		
									.62* [0.10, 1.15]	24.31**



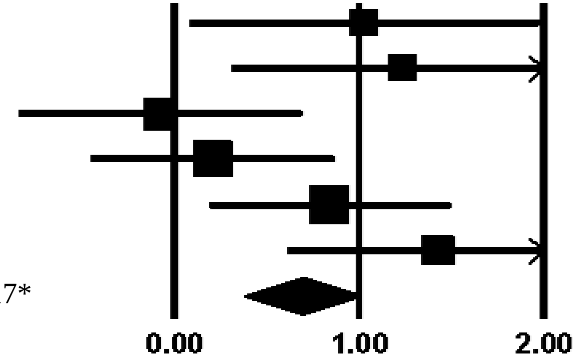
*$p < .05$; ** $p < .001$

Note: Effect size for Cohen's *d*; ROI = Region of Interest; WB = Whole Brain, F = Frontal lobe, C = Central lobe, T = Temporal lobe, P = Parietal lobe, O = Occipital lobe; Overall ES for Hedge's *g*; 95% *CI* = 95% Confidence Interval for Hedge's *g*; *Q* = *Q* statistics.

Table 4

Cohen's *d*, Hedge's *g*, 95% Confidence Intervals, *Q* Statistics, and forest plot for the studies included in the analysis for Theta Power (4-8Hz).

Study	Effect Size (*d*) per ROI						Overall	95% *CI*	Cohen's *g*	*Q*
	WB	F	C	T	P	O	ES (*g*)		[95% *CI*]	
Baumeister et al. (2008)		1.08					1.03	[0.09, 1.97]		
Bertollo et al. (2016)		1.38	1.20				1.23	[0.31, 2.16]		
Cheng et al. (2015)			-0.08				-0.08	[-0.84, 0.69]		
Chuang et al. (2015)		0.21					0.21	[-0.45, 0.86]		
Hunt et al. (2013)	0.86						0.84	[0.19, 1.49]		
Salazar et al. (1990)				1.47			1.43	[0.62, 2.24]		
									.74* [0.26, 1.21]	11.17*



*$p < .05$

Note: Effect size for Cohen's *d*; ROI = Region of Interest; WB = Whole Brain, F = Frontal lobe, C = Central lobe, T = Temporal lobe, P = Parietal lobe, O = Occipital lobe; Overall ES for Hedge's *g*; 95% *CI* = 95% Confidence Interval for Hedge's *g*; *Q* = *Q* statistics.

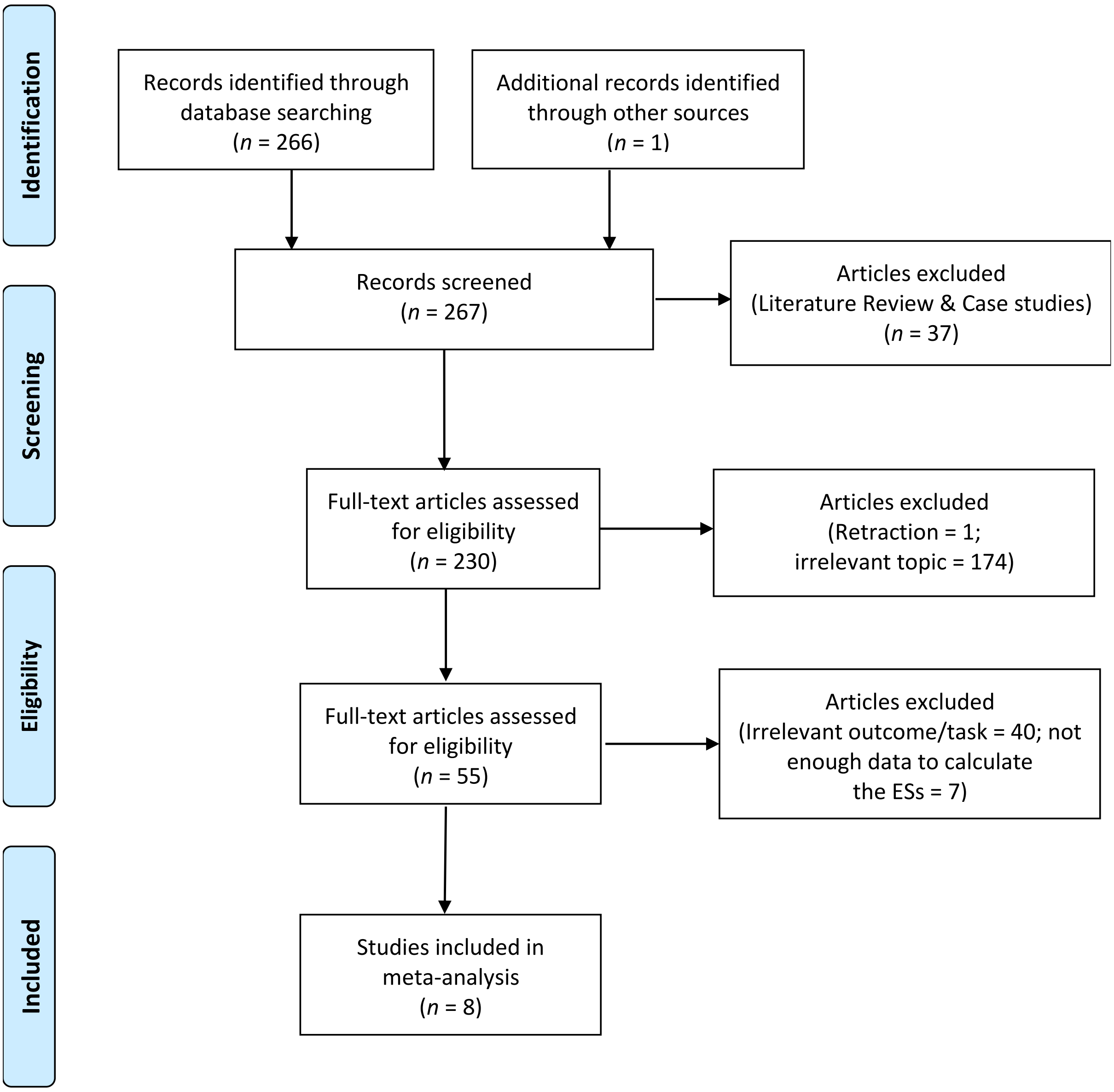


Figure 1. PRISMA Flow-Chart: Search Results

Note: Duplicates were omitted during the search.

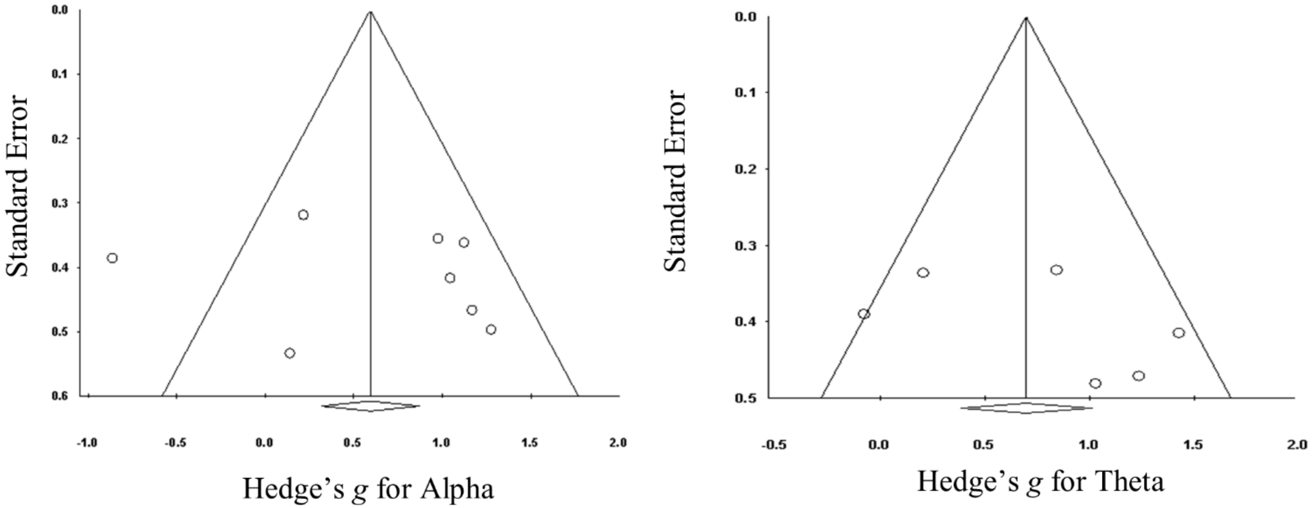


Figure 2. Funnel Plots of Standard Errors and Hedge's g for Alpha (left panel) *and Theta (right panel).*

Table 5

Moderator Analyses for Alpha and Theta Power for Main Analysis, Time of Assessment, and Hypofrontality.

		Alpha (10-13Hz)			Theta (4-7Hz)		
Moderator		Overall ES (*g*)	95% *CI*	*Q*	Overall ES (*g*)	95% *CI*	*Q*
Main Analysis Type	Between-subjects	.89*	[0.13, 1.64]		.60	[-0.15, 1.32]	
	Within-subjects	.35	[-0.42, 1.12]		.91*	[0.17, 1.65]	
	Overall	.62*	[0.09, 1.16]	0.95	.75*	[0.22, 1.27]	0.37
Time of assessment	Before performance	.45	[-0.13, 1.03]		.58*	[0.03, 1.14]	
	Across performance	1.22*	[0.15, 2.30]		1.13*	[0.24, 2.02]	
	Overall	.70	[-0.01, 1.40]	1.53	.74*	[0.26, 1.23]	1.06
Hypofrontality	Frontal lobe	1.06*	[0.25, 1.87]		.38	[-0.18, 0.93]	
	Other lobes	.36	[-0.27, 0.99]		1.08**	[0.52, 1.64]	
	Overall	.66	[-0.02, 1.34]	1.79	.76*	[0.04, 1.41]	3.01

*$p < .05$
** $p < .001$
Note: Overall ES for Hedge's *g*; 95% *CI* = 95% Confidence Interval for Hedge's *g*; *Q* = *Q* statistics.

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