Article

Visuospatial Working Memory Capacity in the Brain After Working Memory Training in College Students With ADHD: A Randomized Controlled Trial

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Abstract

Objective: ADHD has been associated with persistent problems of working memory. This study investigated the efficacy of an intensive and adaptive computerized working memory treatment (CWMT) at behavioral and neural levels. **Method:** College students (n = 89; 40 females) with ADHD were randomized into a standard-length CWMT (45 min/session, 25 sessions, n = 29), shortened-length CWMT (15 min/session, 25 sessions, n = 32), and a waitlist group (n = 28). Both CWMT groups received treatment for 5 days a week for 5 weeks. Lab sessions before and after CWMT assessed electroencephalography (EEG) indicators of working memory, behavioral indicators of working memory performance, and ADHD symptomatology. **Results:** No evidence was found for neural or any other behavioral transfer effects of improvement for the CWMT treatment groups over the active control or waitlist group. **Conclusion:** Our study does not provide evidence for the benefits of CWMT at neural or behavioral levels. *(J. of Att. Dis. 2021; 25(7) 1010-1020)*

Keywords

ADHD, working memory, treatment, randomized controlled trial, EEG, contralateral delay activity

Introduction

ADHD is among the most common childhood neurodevelopmental disorders with global prevalence estimates around 7.2% (~129 million people; Thomas, Sanders, Doust, Beller, & Glasziou, 2015). Longitudinal studies document a high level of persistence of ADHD symptomatology into adulthood (>70%) with severe difficulties reported in occupational, health, and academic domains (Barkley, Fischer, Smallish, & Fletcher, 2002; Uchida, Spencer, Faraone, & Biederman, 2018).

The treatment of ADHD has been challenging. Common treatments for ADHD, such as medication and/or (parent) management treatment, have not been shown to be highly effective in the long run (Jensen et al., 2007; Molina et al., 2009); nor do they appear to directly target the executive functions that frequently co-occur with ADHD (Biederman et al., 2004; Rapport, Orban, Kofler, & Friedman, 2013; Weyandt, Oster, Gudmundsdottir, DuPaul, & Anastopoulos, 2017). This has, in part, contributed to a search for alternative or complementary treatments. One new candidate treatment program, making use of recent advances in information technology, is intensive computerized executive function training. These treatment programs are fully online, home based, relatively cost-effective, and flexible in adapting to individual differences in difficulty level. The training exercises, often marketed as "brain training," are presented as games and are designed to strengthen specific executive function deficits linked to ADHD, such as working memory (Klingberg, 2010).

Neural measures have more recently been explored as outcome measures in the context of treatment studies as they may provide unique perspectives on disorders given that they are theorized to capture the underlying neurobiological mechanisms mediating deficits (Lenzenweger, 2013; Woltering & Shi, 2016). The value of neural measures is also that they, when used in tandem with other measures, can provide incremental validity of the outcome measurement. The goal of this study was to assess the

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efficacy of computerized working memory training (CWMT) and test whether the underlying neural circuits mediating working memory would change in adults with ADHD. We note that the dataset reported in this article presents data on working memory from a larger-scale randomized controlled trial (RCT). Previously reported behavioral and other neural data have been reported elsewhere (Liu, Glizer, Tannock, & Woltering, 2016; Liu, Lishak, Tannock, & Woltering, 2017; Mawjee et al., 2017; Mawjee, Woltering, & Tannock, 2015). Here we present new treatment-related data on behavioral and neural measures derived from samples who completed a visuospatial change detection task yielding measures of working memory filtering efficiency and working memory capacity (please see Supplemental Material—Section 1 for more information on sample composition).

The rationale for our larger-scale RCT study was motivated by three main reasons at the time that our research program was conceptualized in 2010. The first is theoretical models suggesting that executive functions, in particular working memory, are central in ADHD. One of the most influential and comprehensive theoretical models on ADHD proposes that working memory is one of four core executive functions underlying the deficit (Barkley, 1997). Indeed, meta-analytical studies have shown that working memory is impaired in people with ADHD compared with their peers (Kasper, Alderson, & Hudec, 2012; Martinussen, Hayden, Hogg-Johnson, & Tannock, 2005). The second is claims that the capacity of WM is not fixed but can be changed with intensive training (Jaeggi, Buschkuehl, Jonides, & Perrig, 2008; Klingberg, Forssberg, & Westerberg, 2002). This notion was supported by one particular influential study in which reductions in ADHD symptomatology were reported in an RCT using CWMT (Klingberg et al., 2005). The third is initial assertions that this training demonstrated changes in the density of dopamine D1 receptors in prefrontal and parietal brain regions linked to working memory functioning in healthy participants (McNab et al., 2009).

The RCT used the CogMed CWMT program (CogMed; Cognitive Medical Systems AB, Stockholm, Sweden) which has been the most widely used and available CWMT (Klingberg, 2010). To assess treatment effects, we utilized a randomized controlled design with three arms: a standard-length arm (CogMed Working Memory Training [CMWT]: 45 min/session daily for 5 weeks); a shortened-length arm (CMWT: 15 min/session for 5 weeks) that controlled for motivation, engagement, and expectancy of change; and a no-training waitlist group. We note that the complete behavioral results for this sample have been reported elsewhere (Mawjee et al., 2017; Mawjee et al., 2015) and that the novelty of this study is mostly driven by the neural findings and their relationship with the behavioral data. We recruited college students with ADHD as they have been a growing but relatively understudied population. As students, they face an increased demand for self-regulation, time management, and organization to succeed in what is a particularly formational period of their lives (DuPaul, Pinho, Pollack, Gormley, & Laracy, 2017; Gray, Fettes, Woltering, Mawjee, & Tannock, 2016).

To assess working memory, we used a visuospatial change detection task with distractors while participants were hooked up to an electroencephalography (EEG) unit (Vogel, McCollough, & Machizawa, 2005). In short, this paradigm asked participants to remember the colors of squares within an array under three conditions: a low-load (LL) condition (two squares), a high-load (HL) condition (four squares), and a distractor-load (DL) condition (two squares + two circles; *circles were distractors and had to be ignored*), for a brief period of time. A waveform over posterior electrode sites called the contralateral delay activity (CDA) has an amplitude modulated by the numbers of objects (e.g., load condition) being held in memory (for more details, see Vogel & Machizawa, 2004; Vogel et al., 2005). The sensitivity of the CDA waveform to load manipulations can also be used to determine whether irrelevant items unnecessarily consume memory, that is, an index of filtering efficiency of the brain. For example, if the CDA of the distractor condition (two squares + two circles) resembles the LL condition (two squares), it can be concluded that participants' brains effectively filtered out the irrelevant circles and excluded them from storage. However, if the CDA for the distractor condition resembles that of the HL condition (four squares), participants may have failed to efficiently filter out the distractors. A recent meta-analysis supported the relationship between CDA amplitude change with load (CDA-Δ) and filtering efficiency with the visuospatial working memory capacity (Luria, Balaban, Awh, & Vogel, 2016).

Our alternative hypothesis, based on the initial clinical trials preregistration (#NCT01657721), was as follows: We expected behavioral improvements and concomitant neural changes indicative of improved working memory. Stronger effects were expected for standard-length compared with shortened-length training compared with the waitlist group, respectively. Specific hypotheses for neural outcomes at the level of CDA activity were not preregistered and were therefore predictions based on comparative data from this ADHD sample and a matched peer group without ADHD (Gu, Liu, Tannock, & Woltering, 2018). These findings suggested that individuals with ADHD showed *no* difference in CDA amplitude with the load manipulation compared with a typically developing comparison group. We therefore expected an increase in CDA-Δ, that is, a normalization, to be associated with an improvement in the treatment groups. We had no prediction with regard to the neural filtering efficiency.

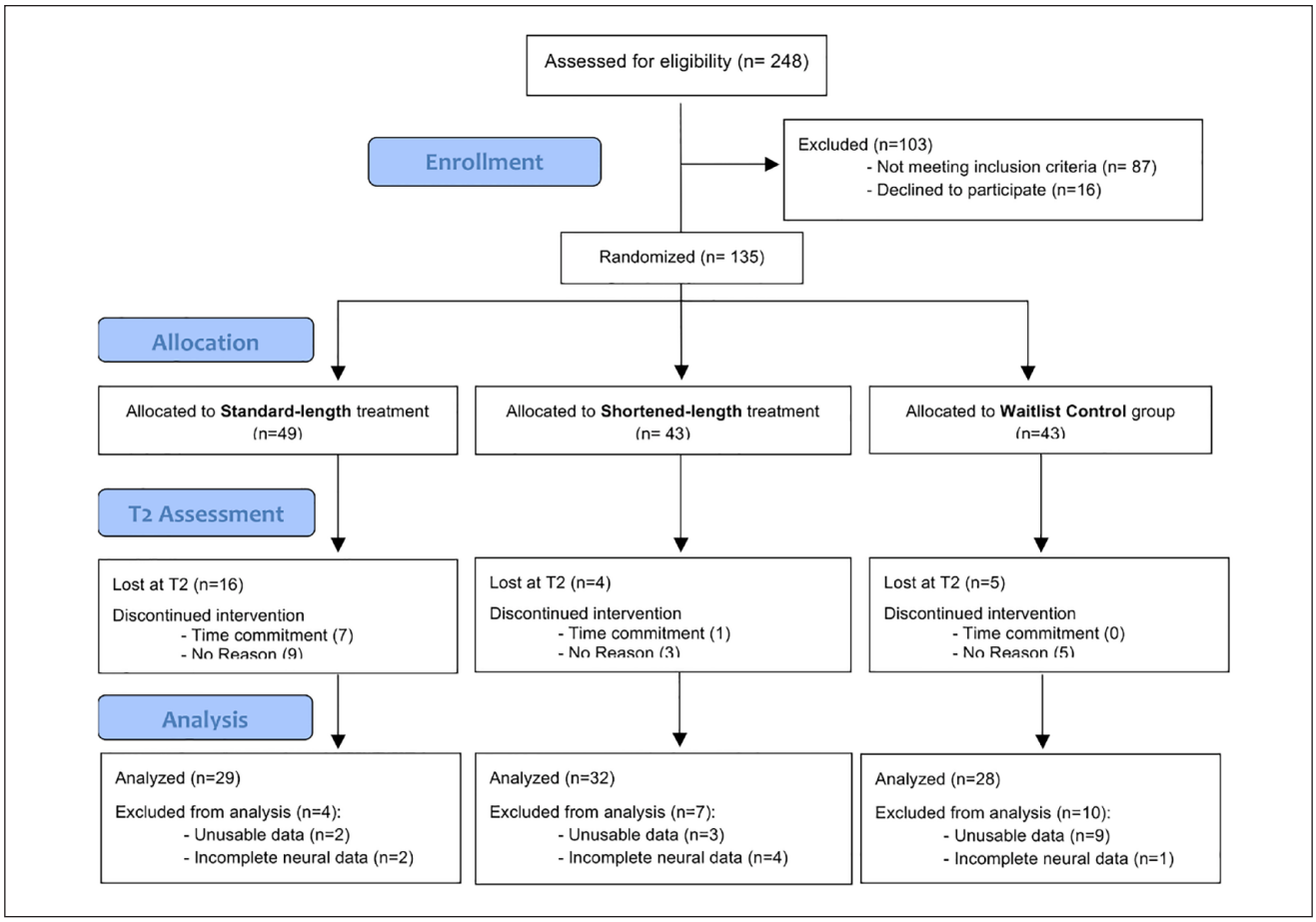

Figure 1. CONSORT flowchart.
Note. Unusable data include machine malfunction and too many artifacts causing less than 10 artifact-free as well as participants not being engaged with the task (e.g., false alarm rates: 100%). Incomplete neural assessment means that participants did not complete the post-training EEG assessment. CONSORT = Consolidated Standards of Reporting Trials; EEG = electroencephalography.

Materials and Methods

Participants

Participants with ADHD were recruited through listserv emails sent from student disability services. Semistructured telephone interviews were conducted to assess the participants' eligibility and validate their current ADHD symptomatology (for details, see Gray et al., 2016; Gray, Woltering, Mawjee, & Tannock, 2014). Inclusion criteria were (a) registered with Student Accessibility/Disability Services with a confirmed diagnosis of ADHD; (b) current symptoms consistent with diagnostic criteria for ADHD as indicated by telephone interview and meeting the criterion scores on the six-item Adult ADHD Self-Report Scale–Part A (ASRS-A); (c) current enrollment in post-secondary education institutions; and (d) age between 18 and 35 years. Exclusion criteria included (a) major neurological dysfunction or psychosis; (b) current use of sedating or mood-altering medication other than stimulant medication provided for ADHD; (c) uncorrected sensory, motor, or perceptual handicap that would prevent use of a computer program; and (d) a history of concussion or traumatic brain injury prior to ADHD diagnosis. More information on the composition of the sample, and its relationship to previously published studies from this project, is provided in Supplemental Material—Section 1.

In accordance with CONSORT (Consolidated Standards of Reporting Trials) guidelines for reporting RCTs, Figure 1 shows the flow of participants through the study and the randomization into three arms. Participants who were excluded from the study were not different from those who completed the training on all demographic, questionnaire, and standardized performance measures before treatment as verified by chi-square and independent *t* tests. The proportion of participants who did not complete the training was similar across the three training groups.

Table 1 describes the basic demographics and participant characteristics for the final sample and broken down per

Table 1. Questionnaire and Demographic Information.

	Standard length		Shortened length		Waitlist control	
	$n = 29$		$n = 32$		$n = 28$	
	M	*SD*	*M*	*SD*	*M*	*SD*
Males/females (*n*)	16/13		18/14		15/13	
Taking medication (*n*)	19		16		14	
Age (years)	24.3	3.4	23.5	3.5	23.5	3.4
WASI-IQ[a]	116.1	10.9	109.8	13.0	115.2	13.2
SA-45 (Global)[a]	60.0	7.4	62.0	8.2	59.1	8.1
Anxiety	59.9	8.3	62.1	8.2	60.3	8.7
Depression	59.8	5.4	59.7	7.4	57.8	7.1
Obsessive–compulsive	69.1	7.9	71.7	8.5	67.0	7.3
Somatization	54.6	6.8	55.6	9.5	53.8	8.5
Phobia	62.7	5.8	63.3	5.7	61.4	4.7
Paranoia	55.1	8.0	56.2	8.5	56.6	7.9
Psychoticism	60.1	4.2	61.1	5.0	61.2	5.3
Post-secondary education (years)	2.4	1.5	2.6	1.3	2.1	1.3
GPA	2.9	0.7	2.9	0.7	3.1	0.7

Note. GPA values are self-reported. WASI-IQ = Wechsler Abbreviated Scale of Intelligence–Intelligence Quotient; SA-45 = Symptom Assessment-45; GPA = Grade Point Average.
[a]Standardized scores.

three arms: standard-length ($n = 29$), shortened-length ($n = 32$), and waitlist ($n = 28$) groups. No statistically significant differences were found on any of these variables when arms were compared. Participants were not required to make changes to their medication treatment for the duration of the study (the lab visits and treatment period). Participants were asked to circle M or F with the prompt "gender," so we cannot disambiguate biological sex from gender identity. No information was collected on race/ethnicity because such information was not ascertained in Canada at the time of the study and, to date, there is no national policy on gathering such data in Canadian-based research (Coteau, 2018; Niemi, Wortley, Yau, & Pruegger, 2015). We acknowledge that this limits the full characterization of our sample.

Procedure

This study was preregistered at ClinicalTrials.gov (registration #NCT01657721) and approved by the Institutional Ethics Boards of the University of Toronto where this study was conducted (protocol reference: #23977). Prior to entering the study, informed written consent was obtained from all participants. During the first, pre-training, testing, all participants came to our laboratory to complete a behavioral assessment and several computerized tasks with EEG. The behavioral assessment was conducted first and included a battery of neuropsychological tests and behavioral rating scales which lasted up to 3 h (see Mawjee et al., 2017; Mawjee et al., 2015, for details). After a break, the EEG assessments began. EEG tasks included, respectively, a resting state task (Woltering, Jung, Liu, & Tannock, 2012), the change detection tasks (Gu et al., 2018, and see described in present paper), a delayed match-to-sample working memory task (Kim, Liu, Glizer, Tannock, & Woltering, 2014; Liu et al., 2016), and a Go-Nogo task (Liu et al., 2017; Woltering, Liu, Rokeach, & Tannock, 2013). Participants were compensated $20 at their first visit (pre-training) session and $150 at their second (post-training) session. After the first lab visit, participants were randomly assigned to three groups: a standard-length training group, a shortened-length training group, and a traditional waitlist group. The two training groups then went through 5 weeks of working memory training with different training intensity (described in more detail in the next section). The waitlist group did not do any training. At 3 weeks after the end of the training program, all participants came back to the laboratory to complete behavioral and EEG assessments identical to the ones in the pre-training assessment.

Working Memory Training Program

The CWMT program (CogMed) was provided by a licensed and independent community psychology service agency. The standard version of CWMT consists of 12 auditory–verbal and visual–spatial working memory tasks. The difficulty level is automatically adjusted to each individual by an adaptive algorithm to ensure that participants are always maximally challenged. The program requires 25 training sessions to be completed in 5 days per week for a period of 5 to 6 weeks. To ensure compliance and address training challenges with the program, a certified CWMT coach completed weekly calls by telephone to monitor and discuss training progress. The research/assessment team and the intervention team were operating independently of one another throughout the study.

Participants in the standard-length group engaged in 45 min of training per day. Those in the shortened-length group engaged in an identical program, however, only trained for 15 min per day. Participants in the waitlist group did not undergo any training. To control for possible effects of individual attention from a coach on participants' motivation, the coach calls were also made to participants in the waitlist control group. During these calls, the waitlist participants were provided with information and resources about working memory and were given the opportunity to discuss their progress at post-secondary education. More details on the training tasks, research design, and the entire battery of behavioral measures used during this project can be found in our previous report that primarily focused on the behavioral aspect of working memory training effects (Mawjee et al., 2017; Mawjee et al., 2015). Furthermore, Liu et al.

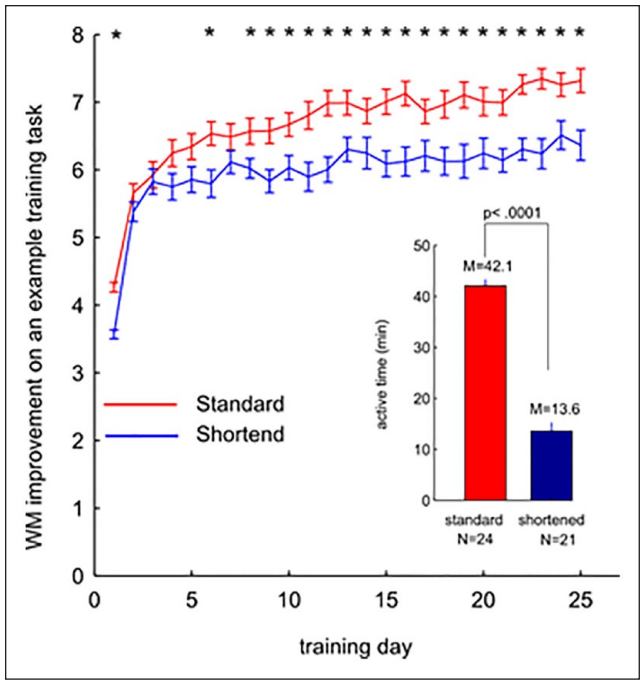

Figure 2. Daily WM improvements for the standard-length ($n = 24$) and shortened-length ($n = 21$) training groups on an example visual–spatial WM training task.
Note. The value of the performance represents the mean working memory span across all trails during a specific training day (session). Embedded bar graphs show that averaged daily active training time was significantly longer for the standard-length than the shortened-length group. Error bars represent standard errors of the mean. "*" indicates the days when the performance was significantly better for the standard-length than the shortened-length group ($p = .0001$-$.037$). Mean performance across all training days was also higher for the standard-length than the shortened-length group, $t(43) = 3.23$, $p = .0024$. WM = working memory.

(2017) provide detailed data on compliance within this sample as monitored by the community psychology service agency confirming that the standard-length group indeed spent the allotted average daily active training time (about 45 min) compared with the shortened-length group (about 15 min). Our training dose manipulation was also verified by data showing participants in the standard-length group outperforming the shortened-length group on the CWMT tasks (see Figure 2 for illustration, from Liu et al., 2017, Supplemental Material).

Measures

Questionnaires and neuropsychological tasks. The numbers of standardized, and well-validated, questionnaires and tasks were assessed before and after the CWMT to capture various levels of transfer (Mawjee et al., 2015). As criterion measures, that is, similar to those trained at CWMT, we assessed the Digit Span Forward and Backward subtests from the Wechsler Adult Intelligence Scale–Fourth Edition (WAIS-IV; Wechsler, 2008). As a near-transfer measure, that is, a working memory measure but dissimilar to those trained, we utilized the pattern recognition subscale of the Cambridge Neuropsychological Testing Automated Battery (CANTAB; Fray, Robbins, & Sahakian, 1996). Finally, as our far-transfer measure, participants completed the Adult ADHD Self-Report Scale (ASRS v1.1; Adler et al., 2012). The Symptom Assessment-45 (SA-45; Maruish, 2004) and the Wechsler Abbreviated Scale of Intelligence–Second Edition (WASI-II; Wechsler, 1999) were assessed at the previsit only to assess additional psychopathology and an estimate of general intelligence.

Neural change detection task. Our visual WM task was adapted from Vogel et al. (2005). E-prime 1.2 software (Psychology Software Tools Inc., Pittsburgh, PA) was used to control stimulus presentation and timing as well as to collect performance measures. In short, participants were shown either a memory array composed of either four colored squares (HL condition; 72 trials), two squares (LL condition; 72 trials), or two squares and two circles (DL condition; 72 trials) per hemifield while they kept their eyes fixated in the middle of the screen. Participants had to memorize the colors of the squares and, after a delay, they were asked to indicate whether one of the squares changed color on a test array (this was the case in 50% of the trials, regardless of the load condition). Our paradigm is explained in more detail in Supplemental Material—Section 2.

Participants' WM capacity (referred to as "*K*") was calculated from their behavioral performance. Similar to Vogel et al. (2005), we used the following formula to calculate *K*: $K = N \times (H - F)$, where K is the visual WM capacity, N is the number of items in the memory array, H is the hit rate, and F is the false alarm rate. By subtracting F from H, we can correct for guessing and obtain a more accurate capacity value. This value was calculated for the *K*[HL], *K*[LL], and *K*[DL] conditions.

Data Processing and Analysis Plan

EEG data acquisition and preprocessing from the change detection task. EEG was recorded with a 128-channel HydroCel Geodesic Sensor Net at a 500 Hz sampling rate, using EGI Net Station standalone software (Electrical Geodesic Inc., Eugene, OR, USA). Data processing was performed similarly to the literature reported on the CDA (e.g., Vogel & Machizawa, 2004; Vogel et al., 2005). In short, after filtering (0.05-30 Hz) and segmenting (400 ms before onset memory array and 1,000 ms after), data were transferred to MATLAB 9.1 (The MathWorks, Inc., Natick, MA) and artifacted using independent component analyses (ICAs; Delorme & Makeig, 2004). Calculation of the CDA wave followed standard procedures (see Supplemental Material—Section 3). Electrode sites (lateral posterior) and time

windows (550-700 ms) for the CDA were chosen a priori based on Gu et al. (2018), where CDA differences with a normal healthy comparison group were found to be maximal. Considering space limitations, we will report more details regarding the artifacting, trial counts, and the computation of the CDA waveforms, in Supplemental Material—Section 3.

CDA-Δ and filtering efficiency were the two measures derived from the CDA waves. CDA-Δ was calculated as the difference between the CDA for the LL and HL conditions (see McCollough, Machizawa, & Vogel, 2007; Vogel et al., 2005). To calculate the filtering efficiency and quantify how efficiently participants can inhibit distractors from entering their limited WM storage, we measured how individuals' CDA amplitudes in the distractors-present condition resembled those in the LL (i.e., two items) condition rather than in the HL (i.e., four items) condition. It was assumed that the closer the distractor CDA amplitudes are to those in the LL condition, the higher the filtering efficiency is. Consistent with the previous studies (Vogel et al., 2005), the following formula was used to calculate this filtering efficiency, $A = (H - D)/(H - L)$, where A is the filtering efficiency and H, L, and D are the CDA amplitudes in the HL, LL, and DL conditions, respectively.

Analysis plan. Our analysis plan was determined a priori. We choose to employ mixed-model repeated-measures analyses of variance (ANOVAs) with Group (three levels: standard length, shortened length, and waitlist) and Time (two levels: pre- and post-treatment) as the between- and within-participant factors, respectively. This analysis was most appropriate as it allowed us to test for the main effects of Group (Condition) and various levels of Time as well as their interactions to determine the treatment effects. Violations of statistical test assumptions (e.g., normality) will be reported. Partial eta-squared (η^2) values were computed to ascertain the effect size. According to Vacha-Haase and Thompson (2004), partial $\eta^2 = .01$ corresponds to a small effect, partial $\eta^2 = .10$ corresponds to a medium effect, and partial $\eta^2 = .25$ represents a large effect. To remove the disproportional effect of potential outliers, data were winsorized to 2.5 standard deviations (see Wilcox, 2011). This was necessary for less than 5% of our variables. We set our significance level at a p value of .05 for all analyses.

Results

Treatment Effects of Questionnaire and Behavioral Data

Performance data during the task, as measured by capacity K, showed a main effect of Time, $F(1, 86) = 6.61$, $p = .012$, $\eta^2 = .07$, and Condition, $F(2, 85) = 244.7$, $p < .000$, $\eta^2 = .85$, with performance improving from pre- to post-treatment and performance in the high load, logically, having higher capacity K values than the LL or DL condition ($p < .001$). Values for the low load were higher than the distractor load ($p < .001$). None of the interaction terms were statistically significant suggesting that the treatment had no effect on the behavioral outcome. The Time by Group interaction term was $F(1, 86) = 1.70$, $p = .19$.

Concerning the questionnaire and neuropsychological tests (please also see Mawjee et al., 2017; Mawjee et al., 2015, for more details on behavioral outcome measures), the criterion measures showed a similar pattern with statistically significant Time by Group interactions for the Digit Span Forward, $F(2, 85) = 5.86$, $p = .004$, $\eta^2 = .12$, and Backward, $F(2, 85) = 6.54$, $p = .002$, $\eta^2 = .13$, tests. Post hoc analyses showed a pattern whereby the standard- and shortened-length training groups improved equally from pre- to post-treatment (p's $< .001$), but the waitlist group showed no improvement. Our near- and far-transfer measures only showed a main effect of Time, with $F(1, 85) = 5.92$, $p = .017$, $\eta^2 = .07$, for the CANTAB pattern recognition, and $F(1, 85) = 13.53$, $p < .001$, $\eta^2 = .14$, for the ASRS, showing better outcomes for both measures from pre- to post-training regardless of the training group. None of the interaction terms were statistically significant suggesting that the treatment had no effect on near- and far-transfer measures of working memory. Table 2 shows the means and standard deviations of behavioral and neural data for Group and Time Point.

Treatment Effects on EEG Data

The CDA-Δ and neural filtering efficiency measures did not show any main effects or interaction effects with $F(1, 86) = 0.97$, $p = .33$, for CDA-Δ, and $F(1, 86) = 2.13$, $p = .15$. Figure 3 shows the CDA waves for each treatment arm and time point broken down per load condition. For simplification, Figure 4 shows the data points of CDA-Δ for each of the treatment arms per time point. Table 2 shows the means and standard deviations of all the aforementioned variables broken down by Group and Time. Corrected for multiple comparisons (criterion set to p lower than .01), the rate of change from pre- to post-treatment in CDA values also did not relate to the rate of change for any of the behavioral variables within each treatment group as measured by correlations. The same pattern of results was found when analyses were rerun, stratifying for sex and medication use.

Discussion

Our results can be aptly summarized by the statement that neural indices of working memory capacity did not show evidence of change as a result of training. These findings, in combination with behavioral findings, show that the CWMT groups did not differ in rate of change compared with a

Table 2. Means and Standard Deviations for Behavioral and Neural Values Broken Down per Group and Time Point.

	Standard-length group ($n = 29$)		Shortened-length group ($n = 31$)		Waitlist group ($n = 28$)	
	Pre-training	Post-training	Pre-training	Post-training	Pre-training	Post-training
Measure	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)
Capacity *K*						
Low load	1.76 (0.27)	1.76 (0.22)	1.73 (0.20)	1.83 (0.12)	1.75 (0.22)	1.76 (0.21)
High load	2.52 (0.76)	2.66 (0.54)	2.55 (0.68)	2.75 (0.52)	2.55 (0.48)	2.54 (0.64)
Distract load	1.60 (0.27)	1.70 (0.22)	1.58 (0.26)	1.74 (0.19)	1.63 (0.26)	1.66 (0.26)
Digit Span						
Forward	9.90 (1.78)	11.66 (2.11)	10.61 (2.00)	11.39 (2.68)	10.39 (2.18)	10.25 (2.12)
Backward	9.41 (2.21)	11.41 (2.23)	9.32 (2.85)	10.74 (2.50)	8.93 (2.05)	8.89 (2.20)
CANTAB pattern	85.1 (21.2)	87.1 (10.2)	86.8 (11.4)	88.4 (10.5)	86.7 (10.1)	91.5 (9.2)
ASRS—total	47.5 (9.8)	45.5 (10.4)	48.5 (8.4)	45.2 (8.8)	49.0 (8.2)	47.0 (8.6)
CDA-FE	0.30 (1.36)	0.80 (1.61)	0.37 (1.12)	0.32 (2.40)	0.13 (1.40)	0.91 (2.75)
CDA-Δ	−0.13 (.57)	0.07 (.75)	−0.24 (0.64)	−0.20 (0.63)	−0.06 (0.62)	0.01 (0.55)

Note. CANTAB = Cambridge Neuropsychological Testing Automated Battery; ASRS = Adult ADHD Self-Report Scale; CDA = contralateral delay activity; FE = Filtering Efficiency.

waitlist group, suggesting that CWMT is not an effective treatment for college students with ADHD.

At a behavioral level, our findings showed that criterion measures, that is, those measures similar to tasks that were incorporated into the training program, were showing an improvement with training. Effects were of similar magnitude for the standard-length (45-min) and shortened-length (10-min) training groups, suggesting no additional benefit from the traditional 45-min training session. Furthermore, these findings also validated that participants adhered to the training and that learning occurred. No effects were found, however, for this specific sample, with the near- or far-transfer tasks, suggesting that CWMT only confers benefits for those tasks that were trained.

Could CWMT have changed underlying neural circuitry of working memory to be more efficient despite a measurable change at a behavioral level? More specifically, is it possible that effects at neural level are subtle but that they do not show up in behavioral measurements or that they capture processes of working memory, such as filtering efficiency, to which most of our traditional behavioral outcome measures are insensitive? Our study did not find support for these notions as our neural findings supported the behavioral ones. The CDA waveforms, which were a reliable index of working memory processing at a neural level (Luria et al., 2016), did not show change after treatment for either of the treatment groups compared with the waitlist group.

Our findings are in line with a more recent body of literature studying the effects of CWMT in college students with ADHD (Liu et al., 2016; Liu et al., 2017; Mawjee et al., 2017; Mawjee et al., 2015) as well as the more general child and adult ADHD population (for recent meta-analytical reports, see Cortese et al., 2015; Melby-Lervåg and Hulme, 2013; Rapport et al., 2013). These studies have generally concluded that CWMT does not appear to increase the working memory capacity nor reliably transfer to untrained tasks of working memory. However, these conclusions are not without controversy. A recent review by Constantinidis and Klingberg (2016) claimed that CWMT does improve on untrained working memory tasks and they proposed a model of neural plasticity based on, in part, increased activity in frontoparietal networks. Our findings contradict these statements and also provided an indirect test of their proposed neural model as the CDA waveform is mediated by the same neural network (Eriksson, Vogel, Lansner, Bergström, & Nyberg, 2015; Luria et al., 2016).

Our findings have implications at a theoretical and a practical level. Theoretically, this study contributes to a growing body of literature discussing the issue of transfer in cognitive treatment (Jaeggi, Buschkuehl, Shah, & Jonides, 2014; Shipstead, Redick, & Engle, 2012; Simons et al., 2016; Stojanoski, Lyons, Pearce, & Owen, 2018) and helps document situations when transfer will and/or will not be likely to occur. In the case of this study, criterion measure, near identical to those trained, did show any improvement, however, and were not affected by the duration of the WM training. Our findings contribute to the neural plasticity literature in suggesting that the activity in frontoparietal networks hypothesized to mediate working memory, and as measured using the CDA, seemed unaffected by CWMT. In this instance, the absence of training effects in performance data of the EEG task (e.g., our capacity *K* measure) matched the neural data. This is not a trivial point, as one could

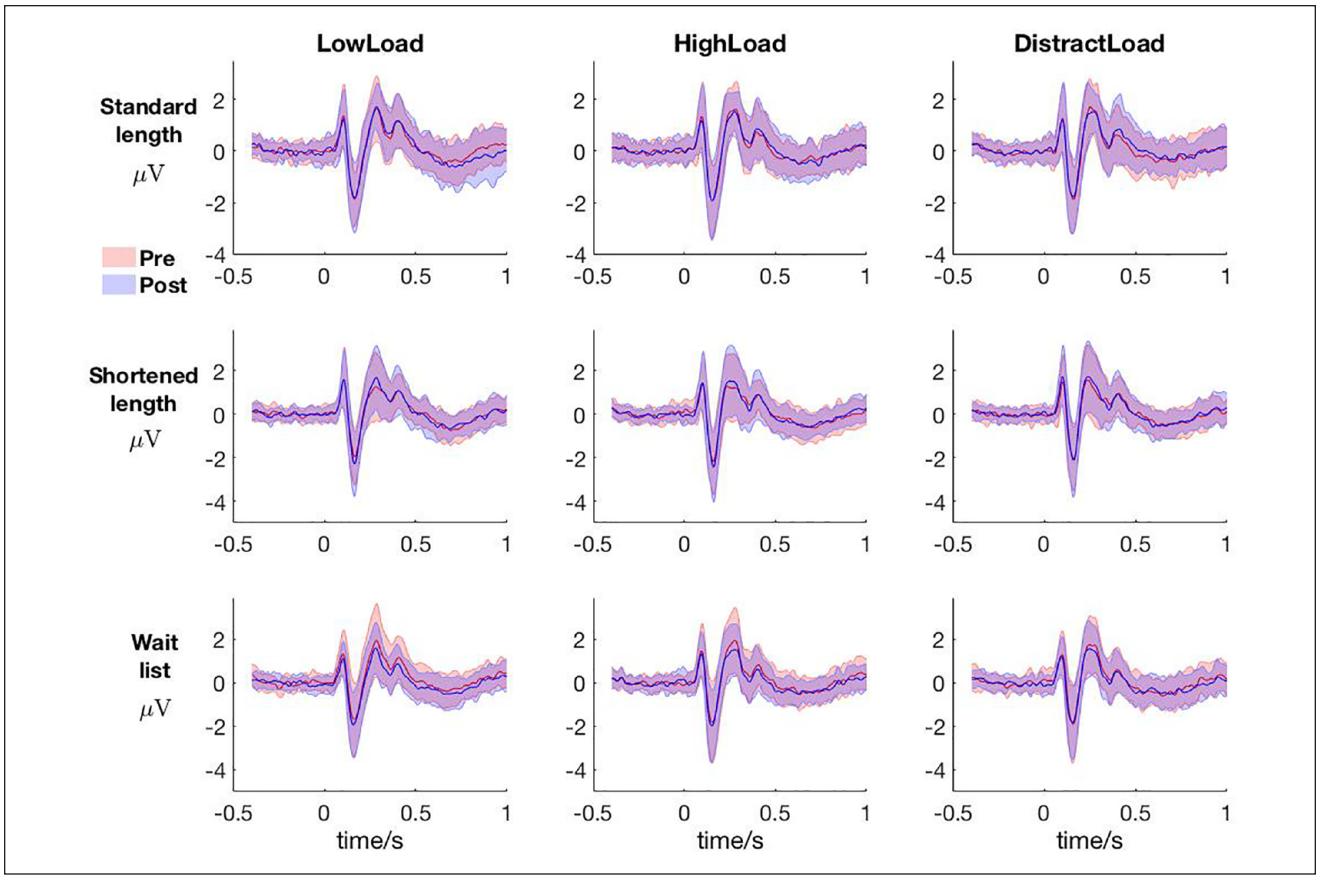

Figure 3. CDA waveforms in microvolts before (pre) and after (post) treatment broken down per load condition (low load, high load, and distractor load) and per treatment group (standard length, shortened length, and waitlist).
Note. CDA = contralateral delay activity.

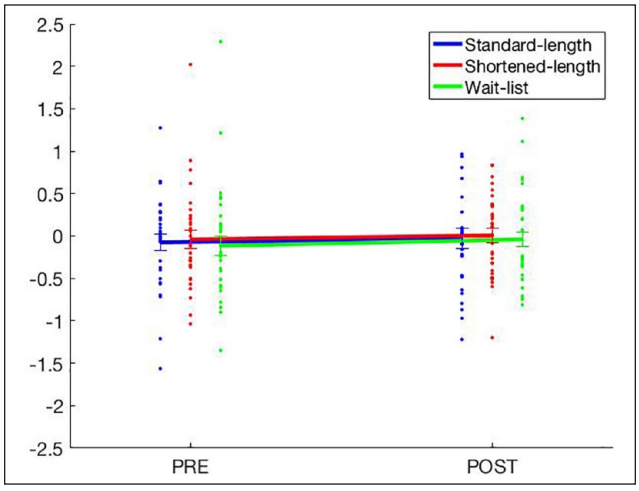

Figure 4. Delta-CDA values at pre- and post-treatment time points for each of the treatment group (standard length, shortened length, and waitlist).
Note. CDA = contralateral delay activity.

theorize those neural working memory networks to have a "general purpose" function and predict that an improvement in one aspect of working memory (e.g., criterion measures) could strengthen, or at least change, this network for other aspects working memory is involved. Our study supports, on the basis of neural activity as measured by EEG, a perspective that promotes a more context-dependent mobilization of neural activity. At a practical level, our study reaffirms the need for a highly critical attitude toward claims from the cognitive training industry that specific executive functions can be trained from computer screens and transferred to benefit operations in everyday life. From a clinical perspective, it appears clear that CWMT is not an effective treatment for college students with ADHD as improvements solely on tasks close to those trained are not meaningful. Future studies, however, could examine sex differences, as well as the combined effects of medication plus CWMT, because our study was likely underpowered to detect such effects.

This study is, to the best of our knowledge, one of the few RCTs directly testing claims that CWMT is changing one's brain in meaningful ways. We conclude that CWMT has not been shown to affect behavioral EEG brain indices of working memory and that CWMT is not an effective treatment for college students with ADHD by testing for treatment effects at various levels of transfer. These findings, using what is currently considered one of the most robust EEG paradigms to measure working memory capacity, contribute to the broader literature on neural plasticity with executive function training and suggest the need for alternative treatment programs.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Supplemental Material

Supplemental material for this article is available online.

References

Adler, L. A., Shaw, D. M., Spencer, T. J., Newcorn, J. H., Hammerness, P., Sitt, D. J., . . . Faraone, S. V. (2012). Preliminary examination of the reliability and concurrent validity of the attention-deficit/hyperactivity disorder self-report scale v1. 1 symptom checklist to rate symptoms of attention-deficit/hyperactivity disorder in adolescents. *Journal of Child and Adolescent Psychopharmacology*, *22*, 238-244. doi:10.1089/cap.2011.0062

Barkley, R. A. (1997). Behavioral inhibition, sustained attention, and executive functions: Constructing a unifying theory of ADHD. *Psychological Bulletin*, *121*, 65-94. doi:10.1037/0033-2909.121.1.65

Barkley, R. A., Fischer, M., Smallish, L., & Fletcher, K. (2002). The persistence of attention-deficit/hyperactivity disorder into young adulthood as a function of reporting source and definition of disorder. *Journal of Abnormal Psychology*, *111*, 279-289. doi:10.1037/0021-843X.111.2.279

Biederman, J., Monuteaux, M. C., Doyle, A. E., Seidman, L. J., Wilens, T. E., Ferrero, F., . . . Faraone, S. V. (2004). Impact of executive function deficits and attention-deficit/hyperactivity disorder (ADHD) on academic outcomes in children. *Journal of Consulting and Clinical Psychology*, *72*, 757-766. doi:10.1037/0022-006X.72.5.757

Constantinidis, C., & Klingberg, T. (2016). The neuroscience of working memory capacity and training. *Nature Neuroscience*, *17*, 438-449. doi:10.1038/nrn.2016.43

Cortese, S., Ferrin, M., Brandeis, D., Buitelaar, J., Daley, D., & Dittmann, R. W., . . . European ADHD Guidelines Group. (2015). Cognitive training for attention-deficit/hyperactivity disorder: Meta-analysis of clinical and neuropsychological outcomes from randomized controlled trials. *Journal of the American Academy of Child & Adolescent Psychiatry*, *54*, 164-174. doi:10.1016/j.jaac.2014.12.010

Coteau, M. (2018, April 23). *Ontario launches provincial standards for race-based data collection*. Retrieved from https://news.ontario.ca/ard/en/2018/04/ontario-launches-provincial-standards-for-race-based-data-collection.html

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*, 9-21. doi:10.1016/j.jneumeth.2003.10.009

DuPaul, G. J., Pinho, T. D., Pollack, B. L., Gormley, M. J., & Laracy, S. D. (2017). First-year college students with ADHD and/or LD: Differences in engagement, positive core self-evaluation, school preparation, and college expectations. *Journal of Learning Disabilities*, *50*, 238-251. doi:10.1177/0022219415617164

Eriksson, J., Vogel, E. K., Lansner, A., Bergström, F., & Nyberg, L. (2015). Neurocognitive architecture of working memory. *Neuron*, *88*(1), 33-46.

Fray, P. J., Robbins, T. W., & Sahakian, B. J. (1996). Neuropsychiatric applications of CANTAB. *International Journal of Geriatric Psychiatry*, *11*, 329-336.

Gray, S. A., Fettes, P., Woltering, S., Mawjee, K., & Tannock, R. (2016). Symptom manifestation and impairments in college students with ADHD. *Journal of Learning Disabilities*, *49*, 616-630. doi:10.1177/0022219415576523

Gray, S. A., Woltering, S., Mawjee, K., & Tannock, R. (2014). The Adult ADHD Self-Report Scale (ASRS). Utility in college students with attention-deficit/hyperactivity disorder. *PeerJ*, *2*, e324. doi:10.7717/peerj.324

Gu, C., Liu, Z. X., Tannock, R., & Woltering, S. (2018). Neural processing of working memory in adults with ADHD in a visuospatial change detection task with distractors. *PeerJ*, *6*, e5601.

Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Perrig, W. J. (2008). Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of Sciences of the United States of America*, *105*, 6829-6833. doi:10.1073/pnas.0801268105

Jaeggi, S. M., Buschkuehl, M., Shah, P., & Jonides, J. (2014). The role of individual differences in cognitive training and transfer. *Memory & Cognition*, *42*, 464-480. doi:10.3758/s13421-013-0364-z

Jensen, P. S., Arnold, L. E., Swanson, J. M., Vitiello, B., Abikoff, H. B., Greenhill, L. L., . . . Conners, C. K. (2007). 3-year follow-up of the NIMH MTA study. *Journal of the American Academy of Child & Adolescent Psychiatry*, *46*, 989-1002. doi:10.1097/CHI.0b013e3180686d48

Kasper, L. J., Alderson, R. M., & Hudec, K. L. (2012). Moderators of working memory deficits in children with attention-deficit/hyperactivity disorder (ADHD): A meta-analytic review. *Clinical Psychology Review*, *32*, 605-617. doi:10.1016/j.cpr.2012.07.001

Kim, S., Liu, Z., Glizer, D., Tannock, R., & Woltering, S. (2014). Adult ADHD and working memory: Neural evidence of impaired encoding. *Clinical Neurophysiology*, *125*, 1596-1603. doi:10.1016/j.clinph.2013.12.094

Klingberg, T. (2010). Training and plasticity of working memory. *Trends in Cognitive Sciences*, *14*, 317-324. doi:10.1016/j.tics.2010.05.002

Klingberg, T., Fernell, E., Olesen, P. J., Johnson, M., Gustafsson, P., Dahlström, K., . . . Westerberg, H. (2005). Computerized training of working memory in children with ADHD—a randomized, controlled trial. *Journal of the American Academy of Child & Adolescent Psychiatry*, *44*, 177-186. doi:10.1097/00004583-200502000-00010

Klingberg, T., Forssberg, H., & Westerberg, H. (2002). Training of working memory in children with ADHD. *Journal of Clinical and Experimental Neuropsychology*, *24*, 781-791. doi:10.1076/jcen.24.6.781.8395

Lenzenweger, M. F. (2013). Thinking clearly about the endophenotype–intermediate phenotype–biomarker distinctions in developmental psychopathology research. *Development and Psychopathology*, *25*, 1347-1357. doi:10.1017/S0954579413000655

Liu, Z. X., Glizer, D., Tannock, R., & Woltering, S. (2016). EEG alpha power during maintenance of information in working memory in adults with ADHD and its plasticity due to working memory training: A randomized controlled trial. *Clinical Neurophysiology*, *127*, 1307-1320. doi:10.1016/j.clinph.2015.10.032

Liu, Z. X., Lishak, V., Tannock, R., & Woltering, S. (2017). Effects of working memory training on neural correlates of Go/Nogo response control in adults with ADHD: A randomized controlled trial. *Neuropsychologia*, *95*, 54-72. doi:10.1016/j.neuropsychologia.2016.11.023

Luria, R., Balaban, H., Awh, E., & Vogel, E. K. (2016). The contralateral delay activity as a neural measure of visual working memory. *Neuroscience & Biobehavioral Reviews*, *62*, 100-108. doi:10.1016/j.neubiorev.2016.01.003

Martinussen, R., Hayden, J., Hogg-Johnson, S., & Tannock, R. (2005). A meta-analysis of working memory impairments in children with attention-deficit/hyperactivity disorder. *Journal of the American Academy of Child & Adolescent Psychiatry*, *44*, 377-384. doi:10.1097/01.chi.0000153228.72591.73

Maruish, M. E. (2004). Symptom Assessment-45 Questionnaire (SA-45). In M. E. Maruish (Ed.), *The use of psychological testing, treatment planning and outcomes assessment* (Vol. 3, 2nd ed., pp. 43-78). Mahwah, NJ: Lawrence Erlbaum.

Mawjee, K., Woltering, S., Lai, N., Gotlieb, H., Kronitz, R., & Tannock, R. (2017). Working memory training in ADHD: Controlling for engagement, motivation, and expectancy of improvement (pilot study). *Journal of Attention Disorders*, *21*, 956-968. doi:10.1177/1087054714557356

Mawjee, K., Woltering, S., & Tannock, R. (2015). Working memory training in post-secondary students with ADHD: A randomized controlled study. *PLoS ONE*, *10*, e0137173. doi:10.1371/journal.pone.0137173

McCollough, A. W., Machizawa, M. G., & Vogel, E. K. (2007). Electrophysiological measures of maintaining representations in visual working memory. *Cortex*, *43*, 77-94. doi:10.1016/S0010-9452(08)70447-7

McNab, F., Varrone, A., Farde, L., Jucaite, A., Bystritsky, P., Forssberg, H., & Klingberg, T. (2009). Changes in cortical dopamine D1 receptor binding associated with cognitive training. *Science*, *323*, 800-802. doi:10.1126/science.1166102

Melby-Lervåg, M., & Hulme, C. (2013). Is working memory training effective? A meta-analytic review. *Developmental Psychology*, *49*, 270-291. doi:10.1037/a0028228

Molina, B. S., Hinshaw, S. P., Swanson, J. M., Arnold, L. E., Vitiello, B., Jensen, P. S., . . . MTA Cooperative Group. (2009). The MTA at 8 years: Prospective follow-up of children treated for combined-type ADHD in a multisite study. *Journal of the American Academy of Child & Adolescent Psychiatry*, *48*, 484-500. doi:10.1097/CHI.0b013e31819c23d0

Niemi, F., Wortley, S., Yau, M., & Pruegger, V. (2015, July 14). *A national policy on the collection of race-based statistics*. Retrieved from https://www.crrf-fcrr.ca/en/component/flexicontent/item/23598-a-national-policy-on-the-collection-of-race-based-statistics

Rapport, M. D., Orban, S. A., Kofler, M. J., & Friedman, L. M. (2013). Do programs designed to train working memory, other executive functions, and attention benefit children with ADHD? A meta-analytic review of cognitive, academic, and behavioral outcomes. *Clinical Psychology Review*, *33*, 1237-1252. doi:10.1016/j.cpr.2013.08.005

Shipstead, Z., Redick, T. S., & Engle, R. W. (2012). Is working memory training effective? *Psychological Bulletin*, *138*, 628-654. doi:10.1037/a0027473

Simons, D. J., Boot, W. R., Charness, N., Gathercole, S. E., Chabris, C. F., Hambrick, D. Z., & Stine-Morrow, E. A. (2016). Do "brain-training" programs work? *Psychological Science in the Public Interest*, *17*, 103-186. doi:10.1177/1529100616661983

Stojanoski, B., Lyons, K. M., Pearce, A. A., & Owen, A. M. (2018). Targeted training: Converging evidence against the transferable benefits of online brain training on cognitive function. *Neuropsychologia*, *117*, 541-550. doi:10.1016/j.neuropsychologia.2018.07.013

Thomas, R., Sanders, S., Doust, J., Beller, E., & Glasziou, P. (2015). Prevalence of attention-deficit/hyperactivity disorder: A systematic review and meta-analysis. *Pediatrics*, *135*, e994-e1001. doi:10.1542/peds.2014-3482

Uchida, M., Spencer, T. J., Faraone, S. V., & Biederman, J. (2018). Adult outcome of ADHD: An overview of results from the MGH longitudinal family studies of pediatrically and psychiatrically referred youth with and without ADHD of both sexes. *Journal of Attention Disorders*, *22*, 523-534. doi:10.1177/1087054715604360

Vacha-Haase, T., & Thompson, B. (2004). How to estimate and interpret various effect sizes. *Journal of Counseling Psychology*, *51*, 473-481. doi:10.1037/0022-0167.51.4.473

Vogel, E. K., & Machizawa, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. *Nature*, *428*, 748-751. doi:10.1038/nature02447

Vogel, E. K., McCollough, A. W., & Machizawa, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, *438*, 500-503. doi:10.1038/nature04171

Wechsler, D. (1999). *Wechsler Abbreviated Scale of Intelligence*. New York, NY: Harcourt Brace.

Wechsler, D. (2008). *Wechsler Adult Intelligence Scale—Fourth Edition (WAIS-IV)*. San Antonio, TX: The Psychological Corporation.

Weyandt, L. L., Oster, D. R., Gudmundsdottir, B. G., DuPaul, G. J., & Anastopoulos, A. D. (2017). Neuropsychological functioning in college students with and without ADHD. *Neuropsychology*, *31*, 160-172. doi:10.1177/0022219407040 00010401

Wilcox, R. R. (2011). *Introduction to robust estimation and hypothesis testing* (3rd ed.). Cambridge, MA: Academic Press.

Woltering, S., Jung, J., Liu, Z. X., & Tannock, R. (2012). Resting state EEG oscillatory power differences in ADHD college students and their peers. *Behavioral and Brain Functions*, *8*(1), Article 33. doi:10.1186/1744-9081-8-60

Woltering, S., Liu, Z. X., Rokeach, A., & Tannock, R. (2013). Neurophysiological differences in inhibitory control between adults with ADHD and their peers. *Neuropsychologia*, *51*, 1888-1895. doi:10.1016/j.neuropsychologia.2013.06.023

Woltering, S., & Shi, Q. (2016). On the neuroscience of self-regulation in children with disruptive behavior problems: Implications for education. *Review of Educational Research*, *86*, 1085-1110. doi:10.3102/0034654316673722

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