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ORIGINAL ARTICLE

The Effects of Emotional Working Memory Training on Worry Symptoms and Error-Related Negativity of Individuals with High Trait Anxiety: A Randomized Controlled Study

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Abstract

Background Trait anxiety is characterized by impaired gating of threat from working memory (WM), allowing unnecessary maintenance of anxious cognitions. Improving filtering efficiency of threatening information through computerized WM training might reduce intrusive, worrisome thoughts.

Methods We randomized high-trait anxious individuals to 9 sessions of high-potency n-back ($n = 19$) or low-potency 1-back ($n = 18$) training to examine their effects on various neurocognitive indices of WM functioning and emotional symptoms.

Results Following the interventions, multilevel modeling analyses revealed both training conditions resulted in significant improvements in attentional (Flanker), WM capacity (operation and spatial span tasks), and WM filtering efficiency (change detection task) measures, and increased N2 amplitudes. However, the high-potency training produced more favorable results at post-training, indexed by larger ERN amplitudes. We also observed significant reductions in trait anxiety and worry symptoms for the high-potency training following the intervention, although, low-potency training caught up at follow-up with comparably reduced symptoms.

Conclusions These results show that emotional WM training can improve neurocognitive processes of attention and WM as well as symptoms of worrying. Overall, this study encourages the development of a standalone or adjunctive cognitive intervention focused on WM for vulnerable populations with high trait anxiety or worry symptoms.

Keywords Emotional working memory training · Trait anxiety · N2 · ERN · n-back

Introduction

Anxiety disorders are associated with several societal and economic costs (Collins et al. 2011; Kessler et al. 2012; Lee and Lotfi 2017), many of which are likely the result of disruptions in normal cognitive functioning (Johnston et al. 2009; Lépine 2002; Robinson et al. 2013; Vytal et al. 2013). Given that evidence suggests these alterations in cognitive functioning serve as a potential risk factor for the development and maintenance of anxiety disorders (Beck and Clark 1997; Mathews and MacLeod 2005; Ouimet et al. 2009), it is likely that treatments aimed at alleviating these cognitive deficits may also reduce anxious symptomology. As such, it is critical to investigate the effects cognitive training has on improving overall cognitive functioning and alleviating anxious symptomology.

Attention is one domain of cognition that has consistently been shown to be affected by anxiety (Bar-Haim et al. 2007; Berggren and Derakshan 2013; Bishop 2007; Cisler and Koster 2010; Derakshan and Eysenck 2009; Eysenck and Derakshan 2011; Eysenck et al. 2007). Attention involves attending to and prioritizing information relevant to current ongoing tasks (Corbetta and Shulman 2002), which is accomplished through the allocation of cognitive resources to enhance processing of specific stimuli in the environment. As proposed by Attentional Control Theory (ACT), anxiety yields deficits in attentional control, reducing the ability to efficiently inhibit distracting information and switch attention towards task-relevant stimuli (for review see Berggren and Derakshan 2013). For example, individuals with elevated anxiety allocate attention towards threatening stimuli, even when they are task-irrelevant (Bar-Haim et al. 2007;

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Bishop 2007). As such, threatening or negatively valanced information occupies attentional resources, resulting in enhanced attentional processing.

Enhanced processing of information leads to the transfer of attended stimuli into working memory (WM; Corbetta and Shulman 2002), another cognitive domain highly intertwined with attention (Awh et al. 2006; Ricker et al. 2018) that is also aversively impacted by anxiety (Moran 2016; Vytal et al. 2013). WM encompasses the ability to store, maintain, and manipulate information over a brief period of time (Baddeley 2012; Cowan 2010, 2017). Given that attention is disrupted by anxiety (Bar-Haim et al. 2007; Berggren and Derakshan 2013; Bishop 2007; Cisler and Koster 2010; Derakshan and Eysenck 2009; Eysenck and Derakshan 2011; Eysenck et al. 2007), there is likely a cascade of events in which deficits in attentional control lead to enhanced storage of threatening information in WM, even if it is task-irrelevant. For example, individuals with elevated trait anxiety engage in excessive allocation of attentional resources toward threat-related stimuli, which allows for this threatening information to enter WM, further maintaining anxious cognitions and subsequently consuming cognitive resources (Bishop 2007; Thiruchselvam et al. 2012). In addition, prior work has found that threatening information is stored in WM to a greater extent than neutral information, even if it is a task-irrelevant distracter (Stout et al. 2013, 2015, 2017). Others have also shown that anxiety is also associated with impaired filtering of neutral distracters from gaining access to WM (Berggren et al. 2017; Moriya and Sugiura 2012; Qi et al. 2014a, b; Stout and Rokke 2010). Therefore, dysfunctional attention towards task-irrelevant stimuli in anxious individuals likely leads to the subsequent storage of this information in WM store, reducing the quantity of WM resources that would normally be dedicated to current ongoing tasks.

Computerized cognitive training holds promise to improve clinical outcomes (Larsen et al. 2019; Owens et al. 2013; Sari et al. 2016; Schweizer et al. 2011, 2013, 2017) through the utilization of a training regimen that improves one's ability to suppress task-irrelevant distracters and increase WM capacity. Although evidence indicates that standard WM training incorporating neutral stimuli has some benefits (Soveri et al. 2017), the overall effectiveness seems to vary (see Melby-Lervåg et al. 2016). As such, others have suggested that WM training incorporating affective stimuli are more likely to yield positive outcomes (Schweizer et al. 2011, 2013, 2017). For instance, Schweizer et al. (2011, 2013, 2017) showed in three different studies that 20 sessions of emotional WM training using an adaptive dual n-back paradigm produced marked behavioral improvement, and yielded behavioral and neural transfer effects on an untrained affective cognitive control task. The emotional n-back task requires constant maintaining and updating of two streams of information in WM (faces and words). Excessive engagement with the emotional valence of stimuli would reduce optimal task performance by using available limited resources at hand. Thus, through repetitive training, subjects would learn to limit irrelevant emotional information gaining access to WM.

Electroencephalography (EEG) and event-related potentials (ERPs) have been shown to provide valuable additional information to behavioral WM indices to evaluate WM training effects which cannot be otherwise obtained (Lotfi et al. 2020; Owens et al. 2013; Sari et al. 2016). With an excellent temporal resolution, ERP data can capture the brain responses at the scale of milliseconds which makes it an ideal method to monitor and reveal precise temporal aspects of underlying cognitive processes such as attentional control processes following WM training. For example, a well-known ERP component, the N2 (i.e., a negative-going ERP component peaking around 200–400 ms post-stimulus at the frontal brain regions) has been shown to reflect better cognitive control in Go/NoGo tasks at larger magnitudes (Falkenstein et al. 1999). Enhanced attentional control associated with increased N2 amplitude has been also shown following 20 sessions of n-back WM training in samples of healthy and multiple sclerosis (Covey et al. 2018, 2019). While the N2 has been implicated in early-state attentional allocation and conflict monitoring (see review by Huster et al. 2013), the error-related negativity (ERN: asymptotes 30–100 ms post-error response at the frontocentral brain regions) has been shown to reflect higher-order monitoring that enables continuous attentional adjustment for enhanced performance in subsequent trials (Cavanagh and Shackman 2015; Wilkowski and Robinson 2016). The ability to detect behavioral errors and adjust subsequent performance is central to WM. For example, Hochman and Meiran (2005) demonstrated that WM capacity is directly related to one's error processing abilities. In accordance with this view, Horowitz-Kraus and Breznitz (2008) showed that when a high WM load was imposed, ERN amplitude was subsequently reduced indicating that error detection activity can be partially influenced by WM load. Additionally, others have reported a positive correlation between WM capacity and the ERN amplitude (Horowitz-Kraus and Breznitz 2009; Jolicœur and Dell'Acqua 1998). Horowitz-Kraus and Breznitz (2009) also found that training to improve WM capacity resulted in enhanced error processing, indicated by a larger ERN. Thus, it is likely that deficits in attentional control may lead to inefficient filtering of task-irrelevant information, subsequently reducing WM capacity and ability to detect errors.

Using a novel emotional WM training (WMT) program for a group of highly anxious individuals, we investigated the WMT effects on (a) early-stage WM processes such as attentional control, filtering efficiency, and the N2 ERP component, and (b) later-stage WM processes such as WM capacity, and error processing (indexed with the ERN). Given that trait anxiety is associated with poor WM capacity (Stout et al. 2013, 2015), we sought to test these hypotheses using a sample of high trait anxious individuals. Specifically, we hypothesized that the high-potency WM training (tWMT = emotional adaptive dual n-back task) compared to a low-potency control WM training (cWMT = emotional non-adaptive dual 1-back task) would show larger improvements in *the WMT Gain Index* (see "WM Training Performance Across Sessions Between the Groups" section) as well as greater transferable effects on untrained tasks of WM, as measured by Automated Complex Span Tasks (Oswald et al. 2015). We hypothesized that tWMT would exhibit larger improvements in behavioral indices of WM filtering efficiency compared to cWMT, as measured by an untrained emotional change detection task (Stout et al. 2015). We also expected the tWMT group to show a larger transfer effect of the training on untrained Flanker task of attentional control, with higher accuracy and faster RT, and increased N2 and ERN amplitudes. Given reports of successful clinical outcomes of WMT (Larsen et al. 2019; Schweizer et al. 2011, 2013, 2017), we also expected reductions in trait anxiety and worry symptoms.

Method

Participants

Participants were recruited from the University of Wisconsin-Milwaukee and the surrounding Milwaukee area (see Fig. 1 for the study flowchart). Three hundred and twenty-two individuals completed an online study consent and pre-screening. They were then invited to in-person assessment sessions if they had access to a high-speed internet connection, did not report any neurological disorders, bipolar disorders, attention deficit disorders, or psychotic disorders, and scored ≥ 44 on the State-Trait Anxiety Inventory-Trait (STAI-T; Spielberger et al. 1983). A cut-point range of 39–55 is suggested for STAI to reflect clinically significant symptoms of anxiety (Kindler et al. 2000; Knight et al. 1983; Kvaal et al. 2005), thus we chose the mid-point as the cutoff for high anxious individuals. Of 117 eligible participants, 49 were recruited and completed a baseline session (BL; tWMT = 22 and cWMT = 27), 37 completed a Post-training session (PT; tWMT = 19 and cWMT = 18), and 33 returned for a 1-month follow-up assessment (FU; tWMT = 17 and cWMT = 16; see Table 1). Participants were randomly assigned to the emotional WM training (tWMT; emotional dual n-back) or the control WM training (cWMT; emotional dual 1-back) group. This study design with the active training group (high-potency) vs. the active control group (low-potency) was adopted from the existing WM training studies, which have also shown that significant training transfer effects to cognitive and emotional domains is only available to high intensity, cognitively demanding and adaptive WM training (Jaeggie et al. 2010, 2014; Schweizer et al. 2011, 2013; Owens et al. 2013; Sari et al. 2016). No significant group differences were observed in gender, age, anxiety, worry, or depression scores and all other outcome measures at the BL phase (all $ps > 0.08$; see Table 1 for self-reported diagnostic history and treatment).

Study Procedures and Materials

At baseline (BL), post-training (PT), and 1-month follow-up (FU), participants completed a set of questionnaires and computerized cognitive tasks. The Flanker task for EEG recording was administered at BL and PT. Consenting and obtaining demographic information was done in the baseline assessment session. Each assessment session (BL, PT, FU) began with participants completing computerized self-report questionnaires (e.g., STAI-T, PSWQ, DASS-21) followed by cognitive tasks (e.g. Automated Span tasks). The EEG setup was administrated afterward and the Flanker and emotional change detection task were completed. Participants underwent nine training sessions at home (up to five sessions weekly) between BL and PT.

Symptoms Self-report Measurements

The STAI-T assesses trait and dispositional anxiety and has been reported to have high test–retest stability ($r = 0.88$) and internal-consistency reliability ($\alpha = 0.89$; Barnes et al. 2002). We used the depression subscale of the Depression Anxiety and Stress Scales (DASS-21; Lovibond and Lovibond 1995) and the Penn State Worry Questionnaire (PSWQ; Meyer et al. 1990) to monitor changes occurring in depression and worry symptom at BL, PT, and 1-month FU. It has been shown that the depression subscale of the DASS has high temporal stability ($r = 0.713$) and high internal-consistency reliability ($\alpha = 0.96$; Brown et al. 1997). Using a nonpatient sample, Meyer et al. (1990) reported that the PSWQ has high internal consistency ($\alpha = 0.93$) and temporal stability ($r = 0.74$) over a period of 2–10 weeks.

The Automated Complex Span Tasks (ACPT)

The Automated Complex Span Tasks (ACPT) consists of three tasks: operation span (O-Span), reading span (R-Span), and symmetry span (S-Span; Oswald et al. 2015). These tasks entailed a processing component (e.g., a math operation) and a storage component (i.e., recalling to-be-remembered letters) to measure WM capacity. All tasks combined took approximately 20–25 min to complete (see Oswald et al. 2015, for more detail about these tasks). The *absolute*

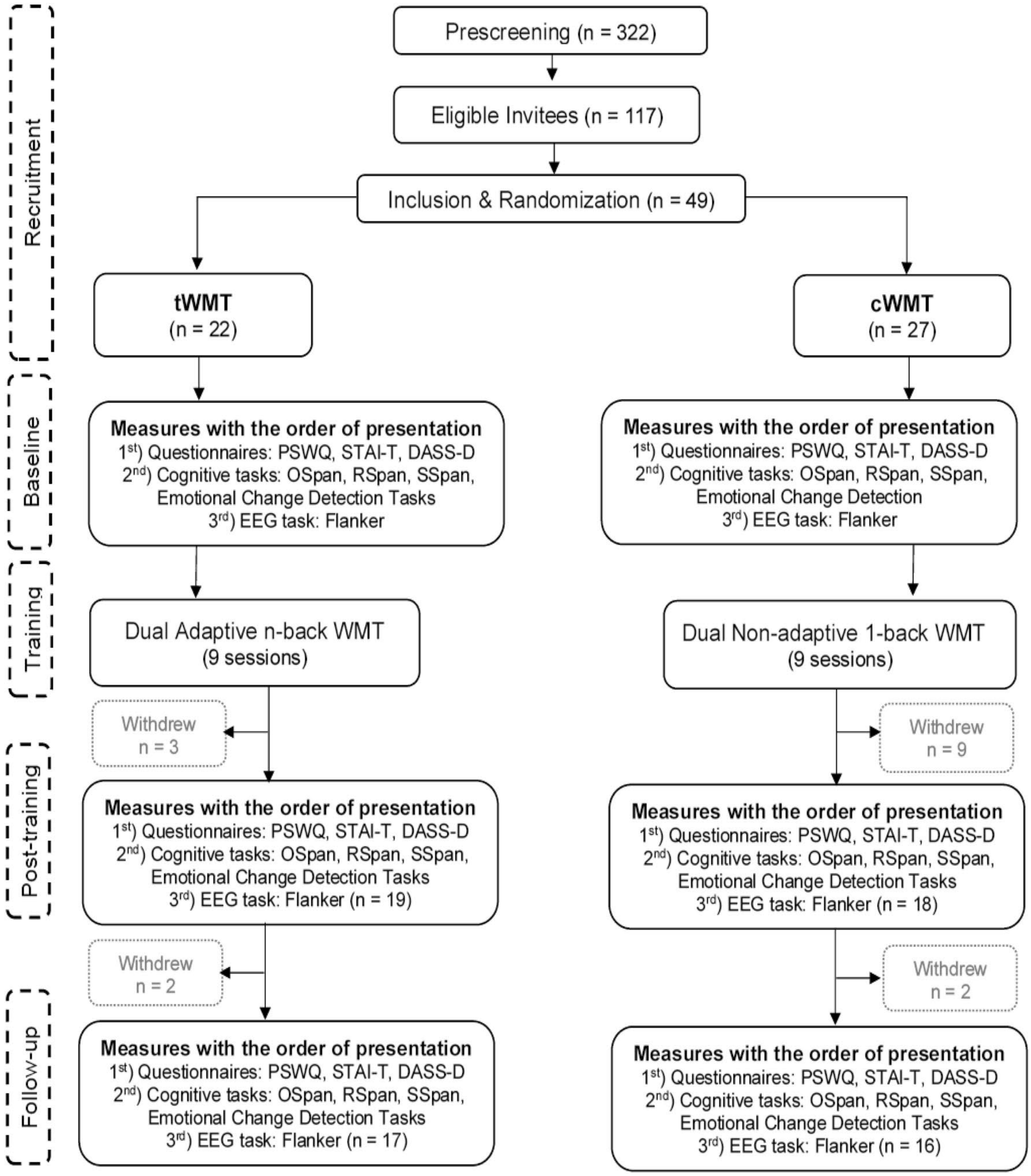

Fig. 1 The study flowchart

storage score (i.e., the sum of correctly recalling all target items in order without error) was used to measure WM capacity for each of the three span tasks.

Flanker Task

Effects of WM training on untrained cognitive tasks have been shown in previous studies (Jaeggi et al. 2008, 2014; Klingberg 2010), particularly, on attentional control processing in anxiety (Sari et al. 2016). An arrow Flanker task was implemented to examine the potential transfer effect of emotional WMT on attentional executive processes. It was composed of 340 trials (20 practice trials) over 5 blocks. Each trial lasted for 1750–2150 ms, beginning with a fixation-cross presented for 950 ms at the center of the screen, replaced by either a congruent (>>>>>) or incongruent (<<><<) set of 5 arrows shown for 200 ms, followed by a jittered fixation-cross ITI for 600–1000 ms. While there was an equal chance of presentation for both condition (congruent or incongruent) and direction (left or right) of the arrows,

Table 1 Baseline demographic and self-reported diagnostic history and treatment

	N-Back ($n=19$)		1-Back ($n=18$)		t-test/χ^2	*p*
	Mean	*SD*	Mean	*SD*		
Age	22.74	4.85	24.89	7.51	1.04	0.31
Gender (% female)	79% ($n=15$)		72% ($n=13$)		0.22	0.63
Ethnicity (% Hispanic)	26% ($n=5$)		11% ($n=2$)		1.39	0.23
Race					0.87	0.35
White	90% ($n=17$)		95% ($n=17$)			
Asian	0% ($n=0$)		5% ($n=1$)			
Multiracial	10% ($n=2$)		10% ($n=2$)			
Education					2.41	0.49
Some High School	32% ($n=6$)		17% ($n=3$)			
Some College	47% ($n=9$)		66% ($n=12$)			
Bachelor's Degree	16% ($n=3$)		17% ($n=3$)			
Master's Degree	5% ($n=1$)		0% ($n=0$)			
Marital status					1.09	0.57
Never married	90% ($n=17$)		84% ($n=15$)			
Married	10% ($n=2$)		10% ($n=2$)			
Divorced/annulled	0% ($n=0$)		6% ($n=1$)			
Total household income					3.25	0.06
< $10K	63% ($n=12$)		44% ($n=8$)			
$10K–$30K	27% ($n=5$)		28% ($n=5$)			
> $30K	10% ($n=2$)		28% ($n=5$)			
Lifetime psychiatric diagnosis (%yes)	47% ($n=9$)		48% ($n=9$)		0.02	0.87
Currently receiving treatment (%yes)	32% ($n=6$)		17% ($n=3$)		1.11	0.29
Psychiatric diagnosis						
Mood disorders	32% ($n=6$)		34% ($n=6$)		0.13	0.91
Sleep-related disorders	5% ($n=1$)		11% ($n=2$)		0.42	0.51
Social phobia, OCD, GAD, or PTSD	38% ($n=7$)		28% ($n=5$)		0.349	0.55
Other psychiatric disorders	5% ($n=1$)		10% ($n=2$)		0.02	0.96
DASS-D-21	11.15	7.69	11.11	7.16	0.01	0.98
STAI-T	60.26	7.93	55.50	9.07	1.71	0.09
PSWQ	62.2	9.1	58.2	10.1	1.21	0.23

DASS-D-21 Depression, Anxiety, and Stress Scales, *STAI-T* State-Trait Anxiety Inventory-Trait, *PSWQ* Penn State Worry Questionnaire

the participants' job was to respond to the direction of the middle arrow quickly and accurately.

Emotional Change Detection Task (CDT)

We hypothesized that emotional WMT might improve filtering efficiency of threat-related distracters gaining access to WM. Thus, we used a modified version of facial change detection task (CDT), adapted from previous studies in our laboratory (Stout et al. 2013, 2015, 2017) and others' (Sessa et al. 2011), which has been shown to reflect the association of high trait anxiety and WM threat-related filtering efficiency deficits. The neutral stimuli of the original version (Vogel et al. 2005) were replaced by an array of 2–4 threatening or neutral faces as to-be-remembered items. Each trial began with a fixation-cross (500 ms), followed by a pair of directional arrows above or below the fixation-cross pointing to the target to-be-remembered hemifield (200 ms). After a short ISI (200–400 ms), an array of faces was presented for 250 ms. Finally, the response probe was shown after a 900 ms delay-period, until a response was made. This task primarily consisted of three conditions (each based on the set size and valence of stimuli: one neutral target (NT1; i.e., the low-load reference-target condition; 120 trials); one neutral target and one fearful distracter (NTFD; i.e., the low-load distraction condition; 90 trials); and one neutral target and one fearful target (NTFT; i.e., the high-load target condition; 120 trials). Each target hemifield had either one or two possible to-be-remembered items, with distraction face surrounded by yellow (or red) borders (counterbalanced) to be ignored. Participants had to attend to the pointed hemifield and remember one or two target faces which were

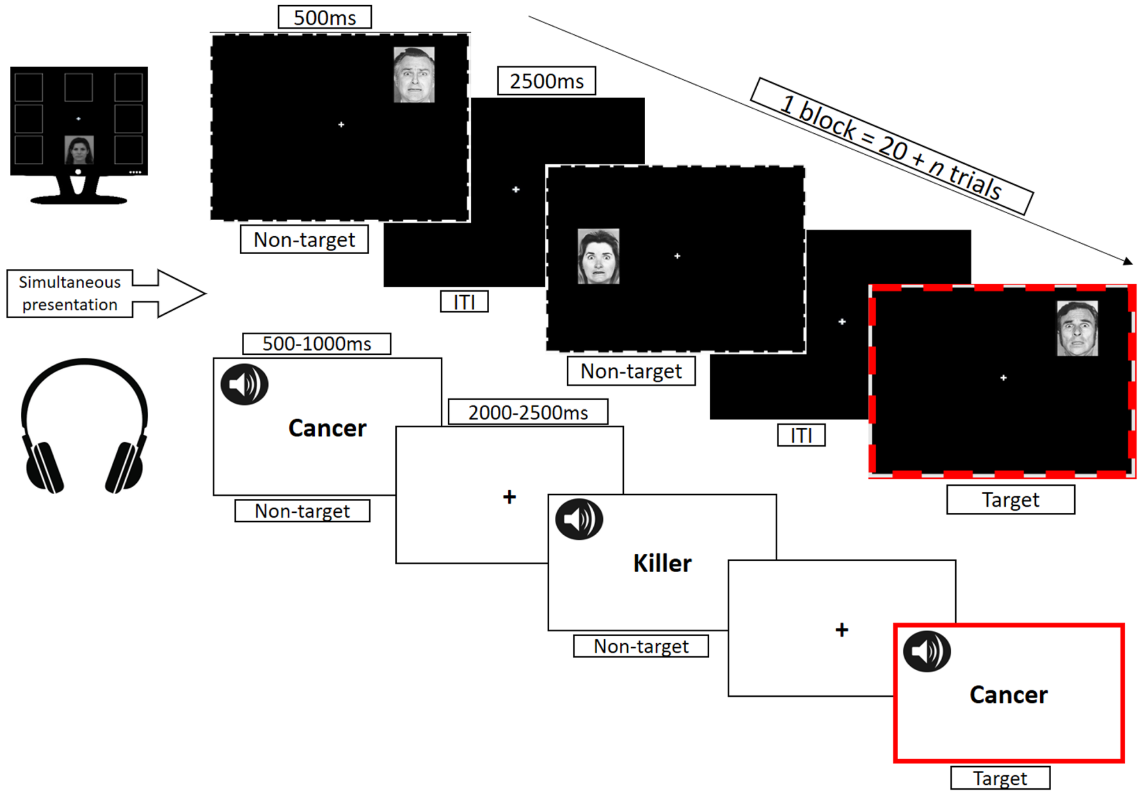

Fig. 2 Emotional dual n-back training. This shows a 2-back block where subjects are instructed to indicate if the location of the face (no identify) and/or the word in the current trial match those presented two trials ago. This figure is adapted from Larsen et al (2019). Affective faces were obtained from Ekman and Friesen (1976)

surrounded by red (yellow) borders and determine if there was a change or not at the probe phase. This design enabled us to measure visual-facial WM accuracy in low-load versus high-load (i.e., NT1 versus NTFT) while assessing gating of threat-related distracters from WM (i.e., Fear Filtering Cost = NTFD – NT1) which indicates the degree of unnecessary storage (for more detail, see Stout et al. 2013, 2015, 2017).

Emotional WMT

We administrated a modified version of the emotional dual n-back training task used previously by our group (Larsen et al. 2019). With a dual-mode feature (visual and auditory) embedded to target constant updating and shifting of WM (Jaeggi et al. 2008), this version of the task replaced neutral visual and auditory stimuli with emotionally-valenced faces and words. Each trial of this task involved simultaneous presentation of a fearful face (500 ms) within a 3-by-3 grid and a fearful word (female voice; e.g., cancer, killer; 500–1000 ms) followed by a fixation-cross ITI (2500 ms; see Fig. 2). To correctly make a response, participants had to constantly maintain the location of the faces and presented words in the *n*-back trial, and match them with both modalities in the current trial at hand. Both training groups (tWMT: *Emotional adaptive dual n-back task*, and cWMT: *Emotional non-adaptive dual 1-back task*) started at the level 1-back; however, while cWMT stayed at this level for the entire course of nine training sessions, tWMT was allowed to move up to the next level with increased difficulty (2-back, 3-back, etc.) if performance was at or above 95% accuracy on both modalities or move down if it was below 75% accuracy. Both training conditions included 20 blocks of 20 + n trials, which lasted around 20–25 min.

ERP Data Acquisition and Preprocessing

EEG was recorded while participants completed the Flanker and the change detection tasks.[1] A DC amplifier and a cap

[1] Over the course of data collection, we identified that event triggers within the change detection task were misplaced due to technical issues of the software, which invalidated part of the ERP data from this task. Thus, we presented only behavioral data from the change detection task. However, it should be noted that behavioral data are intact and their pattern (i.e., the accuracy across different target and distracter conditions) is consistent with existing data (Stout et al 2013, 2015).

with 16-channel shielded leads was used with the following sites according to the 10/20 International System of Electrodes (Fp1 /Fp2, F3/F4, C3/C4, P3/P4, O1/O2, F7/F8, T3/T4, T5, T6, Fz, Cz, Pz; BIOPAC MP-150 System, USA, CA). Impedances were kept below 5 kΩ while raw EEG data were sampled at 250 Hz and referenced to the average value of the left (A1) and right (A2) ear lobe ([A1 + A2)/2]). Horizontal electrooculogram (EOG) activity was recorded from electrodes placed 1 cm to the left and right of the external canthi and vertical EOG activity was recorded from two electrodes placed above and under the right eye. All four EOG electrodes were referenced to an electrode placed on the center of the forehead. Offline data processing was done using EEGLAB (Delorme and Makeig 2004), and ERPLAB (Lopez-Calderon and Luck 2014). EEG data was re-referenced to the average reference (averaged across all channels) and filtered (Butterworth band-pass of 0.1–30 Hz; 24 db/octave). For the N2 ERP component from the Flanker task, correct trials were segmented from − 200 to 800 ms from the onset of the stimulus. N2 amplitudes were calculated as the mean amplitude at Fz in the 200–400 ms post-stimulus onset window, with a baseline-correction of 200 ms (Patel and Azzam 2005). To identify the ERN, error and correct trials were segmented from − 200 to 500 from the onset of the response at the Cz site. The ERN was computed as the mean amplitude 30–70 ms post-response, with a baseline-correction of 200 ms (Cavanagh and Shackman 2015). Trials were automatically rejected if vertical EOG exceeded ± 80 µV and horizontal EOG exceeded ± 60 µV (Luck 2014). Subjects with trials greater than 20% excessive artifact (N2: tWMT = 2 and cWMT = 3; ERN: tWMT = 3, cWMT = 4) were removed from data analyses. The average number of retained trials for the remaining subjects were 94.46% and 92.34% for N2 (tWMT = 17 and cWMT = 15) and ERN (tWMT = 16 and cWMT = 14), respectively. There was no significant difference between the excluded and retained subjects on BL to PT changes scores of our primary outcome measures (i.e. Flanker, CDA, STAI-T, PSWQ, SSpan, *the WMT gain index*; ps > 0.317).

Data Analysis

This study used multilevel modeling (MLM; aka linear mixed models) which is one of the most flexible and robust methods suited for repeated measures designs given its strengths to uniquely account for random effects (subject level variance), handling of missing observations, and modeling of heteroscedasticity (i.e., non-constant variances of the subject level; Brauer and Curtin 2018; Judd et al. 2012). We included all participants who at least finished PT assessment regardless whether they finished all study phases ($n = 37$). In order to determine whether a linear mixed effects model provides a better overall fit for behavioral and questionnaire data over and beyond conventional repeated measure ANOVA, we used χ^2 Likelihood Ratio test to contrast a repeated measure model with no random component against a mixed-effects model. Each participant was treated as random effect, thus, three time observations along with the fix effect of Group (tWMT, cWMT) and dependent variables of interest were nested within participants (Judd et al. 2012). For all of the dependent variables of interest (e.g., PSWQ or OSpan, etc.), χ^2 Likelihood Ratio test for model comparison with and without a random component resulted in a significantly better model fits in favor of mixed effect models (all ps $< 10^{-5}$). Therefore, we proceeded with implementing MLM for the analyses of variables of interest explained in the following section. We used restricted maximum likelihood estimation with an unstructured covariance matrix. Wald approximations were also used to estimate t and F values (with "inner-outer rule" for approximation of denominator of degrees of freedom; Pinheiro and Bates 2000) and to obtain two-tailed p values.

The analyses were implemented using R nlme package which allowed us to model potential heteroscedasticities of residuals among time point observations as it is relevant in longitudinal designs (Hair and Fávero 2019; Pinheiro et al. 2007). In the MLM models, fixed effects were assessed for Group (tWMT, cWMT), Time (BL, PT, FU) and Group × Time. MLM simple effect analyses were used following any significant main or interaction effects. Although the theoretical assumptions of MLM significantly reduces the probability of type I error (c.f., Gelman et al. 2012), we incorporated a highly stringent correction procedure based on the Bonferroni–Holm method (1979) to control for the potential inflation of type I error due to multiple comparisons. We applied the correction procedures for each assessment domain (e.g., self-report questionnaires, cognitive tasks) consisting of inter-related measures. Post hoc power analysis for the final sample of 37, with an observed intraclass correlation of 0.9, a small to moderate effect size of 0.4, three-time measurements (BL, PT, FU) with 0.25 correlation coefficient, and with a significance level of 0.05 (α) was obtained at 0.8 (Magnusson 2017). Finally, the Cohen's d method explained in Swainston and Derakshan (2018) was used to obtain effect sizes driven by a F-test with the following form: $d = 2 * \sqrt{(F/df)}$.

To account for the underlying WM improvements through the training sessions, we generated *the WMT gain index* based on the multiplication of average obtained n by the overall accuracy performance for a session, such that a higher score indicated greater improvement after the completion of training. This index helped us index the potency of the WM training across the high-potency (n-back) and low-potency (1-back) training versions by taking into account the weights of averaged achieved n (potency) and the overall accuracy performance (accuracy) given a session.

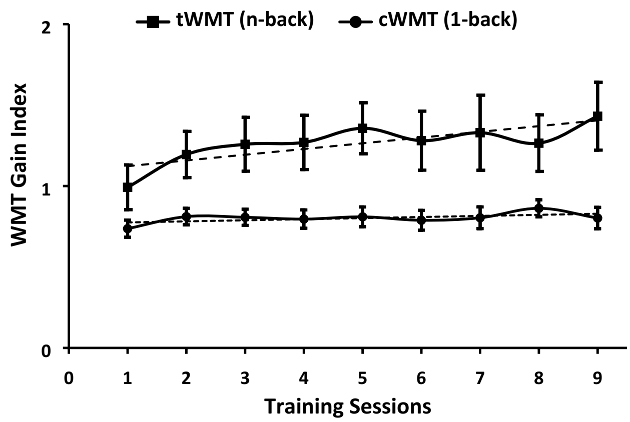

Fig. 3 Average n-back Performance Gain across Training Sessions. The n-back gain index is calculated based on the average n within the given training session multiplied by its overall accuracy. A larger WMT gain index demonstrates a larger training gain. Error bars show standard errors of the mean

Results

WM Training Performance Across Sessions Between the Groups

An independent samples *t*-test showed a significant group difference in the average *WMT gain index* across all 9 sessions [$t(34)=3.77$, $p<0.001$]. The tWMT group ($M_{1stSession}=0.99$, $SD_{1stSession}=1.43$; $M_{9thSession}=1.43$, $SD_{9thSession}=0.63$; Fig. 3) showed gradual increment of the gain index (44.4%) as the training progressed over time relative to small change (9.2%) for the cWMT group ($M_{1stSession}=0.76$, $SD_{1stSession}=0.22$; $M_{9thSession}=0.83$, $SD_{9thSession}=1.43$; Fig. 3).

Worry, Trait Anxiety, and Depression Symptom Change over Time Between the Groups

Using the PSWQ total as the dependent variable, the MLM analyses showed no significant main effect of Group or Time, but there was a significant interaction effect of Group (2 levels; tWMT, cWMT) by Time [3 levels; BL, PT, FU; $F(2, 66)=5.91$, $p=0.01$, *Cohen's* $D=0.59$]. Simple main effect contrasts revealed tWMT compared to cWMT achieved a significantly greater reduction in the PSWQ total score at PT after controlling for BL [$t(64)=2.89$, $p=0.01$]. There was no such a result at FU. However, the overall sample showed a significant reduction in worry scores at FU relative to their respective BL scores [$t(64)=2.89$, $p=0.01$; Table 2].

A similar analysis on STAI-T scores revealed there was no main effect of Group, but there was a main effect of Time [$F(2, 66)=11.18$, $p=0.0001$, *Cohen's* $D=0.82$] and a significant interaction effect of Group by Time [$F(2, 66)=3.41$, $p=0.03$, *Cohen's* $D=0.45$]. Simple main effect analyses showed tWMT vs. cWMT group achieved a significantly greater reduction in trait anxiety at PT after controlling for BL [$t(64)=2.76$, $p=0.007$], with no such an effect at FU. However, there was an overall significant reduction in trait anxiety at FU assessment phase relative to BL [$t(64)=4.8$, $p=10^{-4}$; Table 2].

Using DASS-Depression as the dependent variable, we did not observe a significant main effect of Time, nor a significant interaction effect of Group by Time. These results indicated that neither training conditions significantly affected depression symptoms within the study timeline.

Additionally, we examined the correlation between *the WMT gain index* obtained over the duration of training and the changes that occurred in worry symptom severity from BL to PT (quantified as the contrast between the BL and PT scores). Results showed a non-significant but medium-to-large correlation between them for the tWMT group [$r(16)=0.43$, $p=0.07$; see Fig. 4], which indicates that the amount of training progress achieved by participants (as assessed by *the WMT gain index*) tended to be positively associated with the BL–PT changes scores in worry symptoms. Such a correlation pattern was not seen for the cWMT group [$r(16)=-0.25$, $p=0.32$; see Fig. 4].

OSpan, RSpan, and SSpan Score Change over Time Between the Groups

We observed a significant main effect of Time for OSpan scores [$F(2, 64)=6.58$, $p=0.006$, *Cohen's* $D=0.64$; Table 2]. Contrast analyses revealed that the overall sample showed significant OSpan improvements after the training at PT [$t(61)=4.2$, $p=004$] and 1-month follow-up [$t(61)=2.2$, $p=04$] when contrasted against BL. There was no significant Group by Time interaction for OSpan. A similar analysis on the RSpan did not show a significant main effect of Time, nor a significant interaction of Time by Group. The final set of analyses on SSpan yielded no significant main effect of Time (BL vs. PT). However, there was a significant Group by Time effect [$F(2, 64)=4.4$, $p=0.03$, *Cohen's* $D=0.52$]. Follow-up group contrast indicated that the tWMT group outperformed the cWMT group in improving the Spatial Span performance at PT, following the nine sessions of emotional WM training [$t(61)=2.23$, $p=0.02$; Fig. 5]. Although both groups showed larger SSpan scores at 1-month follow-up relative to BL, such improvements were not statistically significant (Table 2).

Flanker Test Scores Change over Time Between the Groups

We used the Flanker test to examine whether the training effect went beyond the general WM domain and affected

Table 2 Statistical data in BL, PT, and FU for the tWMT and cWMT groups

Categories	Measures	Group	Baseline	Posttest	Follow-Up
Emotion measures	STAI-T[a]	cWMT	55.5 (9.1)	54.4 (8.7)	53.2 (3.3)
		tWMT	60.2 (7.5)	56.5 (7.4)	56.7 (7.9)
	PSWQ[a]	cWMT	58.2 (10.1)	60.3 (8.9)	57 (9.1)
		tWMT	62.2 (9.1)	56.5 (11.7)	58.6 (11.4)
	DASS-D[a]	cWMT	11.1 (7.1)	11.1 (8.4)	10.2 (9.5)
		tWMT	11.1 (7.6)	9.6 (6.7)	10.1 (8)
Automated complex span tasks	OSpan[b]	cWMT	14.6 (10.1)	18.2 (9.7)	18.6 (9.3)
		tWMT	17.9 (6.6)	22.3 (9.4)	20.1 (10.5)
	RSpan[b]	cWMT	13.7 (8.4)	17 (8.8)	17.3 (8.7)
		tWMT	18.6 (8)	16.2 (9.1)	17.5 (9.9)
	SSpan[b]	cWMT	9.5 (5.3)	8.2 (4.2)	10.2 (7.9)
		tWMT	8.2 (3.9)	11.8 (6.2)	11 (7.4)
Flanker	Cong_ACC%	cWMT	89.4 (22.2)	91.6 (22.6)	96.4 (2.7)
		tWMT	96.1 (3.8)	98 (2.1)	97.8 (2.3)
	Incong_ACC%	cWMT	78.1 (19.5)	80.7 (19.8)	83.2 (8.3)
		tWMT	81.3 (11.1)	86.1 (9.3)	88.8 (7.1)
	Cong_RT	cWMT	390.2 (54.4)	378.14 (52.8)	368.1 (54.2)
		tWMT	392.4 (53.3)	370.5 (37.3)	374.8 (31.1)
	Incong_RT	cWMT	435.3 (58.5)	427.3 (58.2)	405.2 (53.5)
		tWMT	448.2 (62.3)	421.8 (49)	417.2 (27.2)
Emotional change detection task	NT1_ACC%	cWMT	91.9 (5.4)	92 (7.5)	89.3 (9.1)
		tWMT	92.1 (4.4)	91.3 (6.5)	93.9 (4.5)
	NTFD_ACC%	cWMT	81.4 (10)	86.5 (9.1)	85.9 (8.9)
		tWMT	83.5 (7.2)	86.3 (8.6)	88.4 (8.7)
	NTFT_ACC%	cWMT	72.5 (8.5)	72.3 (8.5)	72.3 (10.1)
		tWMT	71.6 (6.8)	72.7 (7.7)	72.3 (6.8)
	Fear14FilterCost_ACCd	cWMT	9.8 (6.8)	5.5 (7.3)	3.4 (7.9)
		tWMT	8.6 (6.8)	5.1 (5.3)	5.5 (6.2)

Standard deviations and degrees of freedom are in parentheses

tWMT n-back Training Group, *cWMT* 1-back Control Group, *STAI-T* State Trait Anxiety Inventory-Trait version, *PSWQ* Penn State Worry Questionnaire, *DASS-D* Depression, Anxiety, Stress Scales-Depression, *O/R/SSpan* Operation/Reading/Spatial Span Task, *Cong/Incong_ACC%* Congruent/Incongruent Accuracy Percentage, *NT1/NTFD/NTFT_ACC%* Neutral Target/Neutral Target Fear Distractor/Neutral Target Fear Target Accuracy Percentage, *FearFilterCost_ACCd* Fear Filtering Cost Accuracy Difference

[a]Depicts a scale score; higher scores show greater difficulties

[b]Depicts a measure score; lower scores show greater difficulties

attentional control. For Flanker congruent and incongruent accuracies, we observed a significant main effect of Time [Congruent: $F(2, 55) = 7.2$, $p = 0.0001$, *Cohen's* $D = 0.72$; Incongruent: $F(2, 55) = 4.22$, $p = 0.02$, *Cohen's* $D = 0.55$; Table 2], indicating an overall increase in accuracy. Contrasted against BL, follow-up comparisons showed an overall significant improvement in congruent accuracy only at PT [$t(55) = 3.37$, $p = 0.003$] an overall significant improvement of Incongruent accuracy at both PT [$t(55) = 2.51$, $p = 0.02$] and FU [$t(55) = 2.47$, $p = 0.02$]. This result indicated the increased accuracy was significantly maintained at FU only on the more cognitively taxing condition (incongruent) (Table 2). Using Flanker RTs as the dependent variable, there was a significant main effect of Time for both the congruent and incongruent conditions with no significant Group by Time effect, showing an overall faster RT after the training for both tWMT and cWMT [Congruent: $F(2, 55) = 5.35$, $p = 0.007$, *Cohen's* $D = 0.62$; Incongruent: $F(2, 55) = 5.88$, $p = 0.008$, *Cohen's* $D = 0.65$; Table 2]. Simple effect analyses revealed both conditions showed an overall significant faster RT at PT [congruent: $t(55) = 3.21$, $p = 0.004$; incongruent: $t(55) = 2.51$, $p = 0.01$] and FU [congruent: $t(55) = 2.63$, $p = 0.01$; incongruent: $t(55) = 3.5$, $p = 0.001$] when contrasted against BL. This result confirmed that both groups showed statistically faster Flanker RT at PT and 1-month FU.

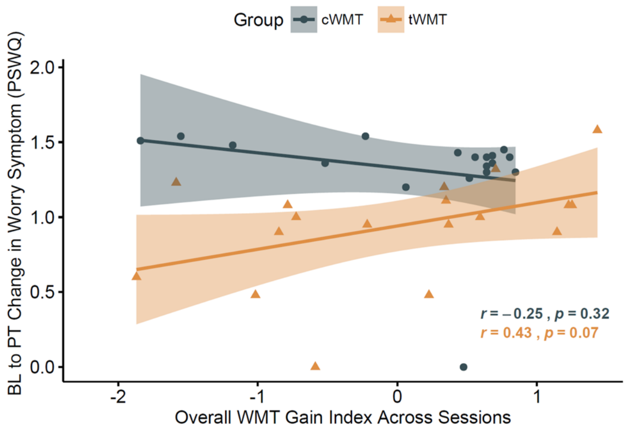

Fig. 4 Association between Improved WM and Worry Symptom (PSWQ) for tWMT and cWMT. The orange line shows a strong but non-significant association between the BL-to-PT change scores on the PSWQ and *the WMT gain index* (standardized: larger values indicates larger WMT gain throughout the training) for tWMT. No such a pattern was observed for cWMT. Shaded area represents confidence intervals

Change Detention Task Score Change over Time Between the Groups

For the CDT we observed increased WM accuracies across all conditions (NT, NTFD, NTFT) at PT and FU, however, the statistically significant effect of Time was limited only to the NTFD condition [$F(2, 55) = 10.08$, $p = 10^{-3}$, *Cohen's D* $= 0.85$]. Nevertheless, we used Fear Filtering Cost (i.e., NTFD − NT1) as our primary index to measure gating of threat-related distracters from WM and obtain the degree of unnecessary storage (Stout et al. 2013, 2015). As such, we found reduced fear processing costs at both PT and FU for the entire sample. Accordingly, using Fear-Filtering Cost as the dependent variable, we observed a significant main effect of Time [$F(2, 55) = 10.22$, $p = 10^{-4}$, *Cohen's D* $= 0.86$]. Follow-up comparisons demonstrated an overall significant reduction at PT [$t(55) = 3.55$, $p = 0.001$] and FU [$t(54) = 2.92$, $p = 0.001$]. This finding indicated that the overall sample showed significant improvements in filtering irrelevant, fearful distracters from entering WM. However, there was no significant Group by Time effect for either time contrasts.

We also examined whether there was any association between the improved WM performance via CDT from BL to PT (quantified as the contrast between BL and PT on the overall averaged CDT accuracy) and *the WMT gain index* obtained over the duration of training. We found that as *the WMT gain index* increased, so did the overall WM accuracy performance following the WM training with a significant correlation [$r(15) = 0.56$, $p < 0.02$] in the tWMT. In contrast, cWMT demonstrated a non-significant correlation [$r(16) = 0.23$, $p < 0.23$]. This result highlights that higher practice on emotional WM n-back training is correlated with larger improvement in other untrained, yet relevant, WM tasks.

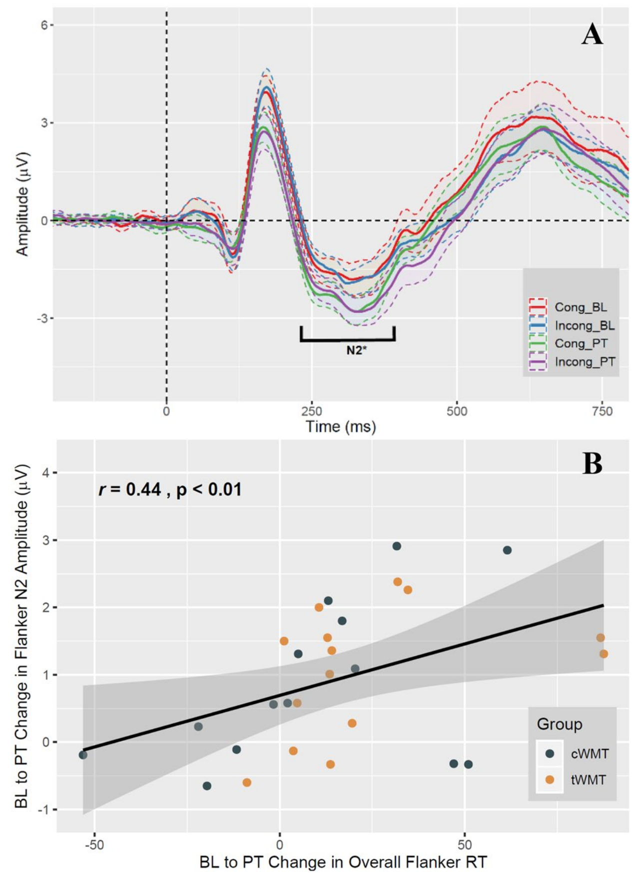

Fig. 5 **a** Grand Average Waveforms from Correct Trials of Flanker Task across Time. Figure 5a showed that both tWMT and cWMT groups displayed the overall BL-to-PT increase in N2 amplitudes in both congruent and incongruent trial types at the frontal region (Fz). Dashed, shaded areas are representing confidence intervals. *Cong_BL* congruent trials at BL, *Incong_BL* incongruent trials at BL, *Cong_PT* congruent trials at PT, *Incong_PT* incongruent trials at PT. Asterisk indicates $p < 0.05$. **b** Association between Improved RT Performance (Flanker) and increased N2 amplitude (Flanker) after the Training. The black line shows a significant correlation between the BL-to-PT change scores on the N2 amplitude (averaged correct trials; a larger value shows a larger N2 magnitude) and the BL-to-PT change scores on Flanker RT (a larger value indicates a larger RT reduction) across both groups. Shaded area represents confidence intervals

ERP Results for Flanker Task (N2 and ERN)

For both congruent and incongruent trials, we found a similar pattern of increased N2 amplitudes from BL to PT across both groups. The trial type did not show any interaction effects with Time or Group. Thus, we conducted the ERP analysis by averaging data across congruent and incongruent trials. We analyzed N2 at Fz electrode (200–400 ms post-stimulus onset averaged across all correct trials) and ERN at Cz electrode (30–70 ms averaged across all post-error response) at the BL and PT assessment phases. We found a significant main effect of Time (BL vs. PT) on the N2 amplitude [$M_{N2\_BL} = -0.98$, $SD_{N2\_BL} = 2.31$; $M_{N2\_PT} = -1.95$, $SD_{N2\_PT} = 1.91$; $F(1, 30) = 17.49$, $p = 0.0002$, *Cohen's D* = 1.52; Fig. 5a]. We found no significant Group by Time effect. This finding highlights that the overall sample showed a significantly larger magnitude of N2 component after the WM training, suggesting improved overall efficiency in attentional control. In line with the result, the increased N2 amplitude from BL to PT (averaged across all correct trials) is positively associated with a faster Flanker RT following the WM training [averaged across all correct trials, $r(30) = 0.36$, $p < 0.008$, see Fig. 5b].

Moreover, while we observed that ERN magnitude increased for tWMT after the training ($M_{ERN\_BL} = -3.36$, $SD_{ERN\_BL} = 4.81$; $M_{ERN\_PT} = -4.99$, $SD_{ERN\_PT} = 3.34$), there was no increase in ERN for cWMT ($M_{ERN\_BL} = -1.82$, $SD_{ERN\_BL} = 2.53$; $M_{ERN\_PT} = -0.82$, $SD_{ERN\_PT} = 2.48$). Using ERN amplitudes at Cz electrode for error trials as the dependent variable, we observed no significant main effect of Time, or Group × Time interaction effect. However, it should be noted that the Group by Time interaction showed a large effect size, with a trend for tWMT to show greater ERN magnitude than cWMT, $F(1, 28) = 4.17$, $p = 0.0506$, *Cohen's D* = 0.78 (large effect) (Fig. 6a, b).

Additionally, we examined the correlation between the BL-to-PT change scores of ERN amplitude (quantified as the contrast between the BL and PT scores) and *the WMT gain index* obtained over the duration of training. We found a non-significant but large correlation between them for the tWMT group [$r(15) = 0.51$, $p = 0.054$; see Fig. 7a], which indicates that the amount of training progress achieved by participants (as assessed by *the WMT gain index*) was accompanied by the magnification in ERN amplitudes following the training. Such a correlation pattern was not seen for the cWMT group [$r(15) = -0.25$, $p = 0.32$; see Fig. 7a]. Importantly, we also observed that the magnification in ERN amplitudes following the training was strongly associated with changes in spatial WM (SSpan) scores from BL to PT only for tWMT, although, it was not significant, however, the effect size was medium [$r(15) = 0.48$, $p = 0.06$; see Fig. 7b]. Together, these findings demonstrated that in this study sample the improvement in WM processes following the training (as assessed by two WM-related measures) is positively associated with the changes in ERN magnitude.

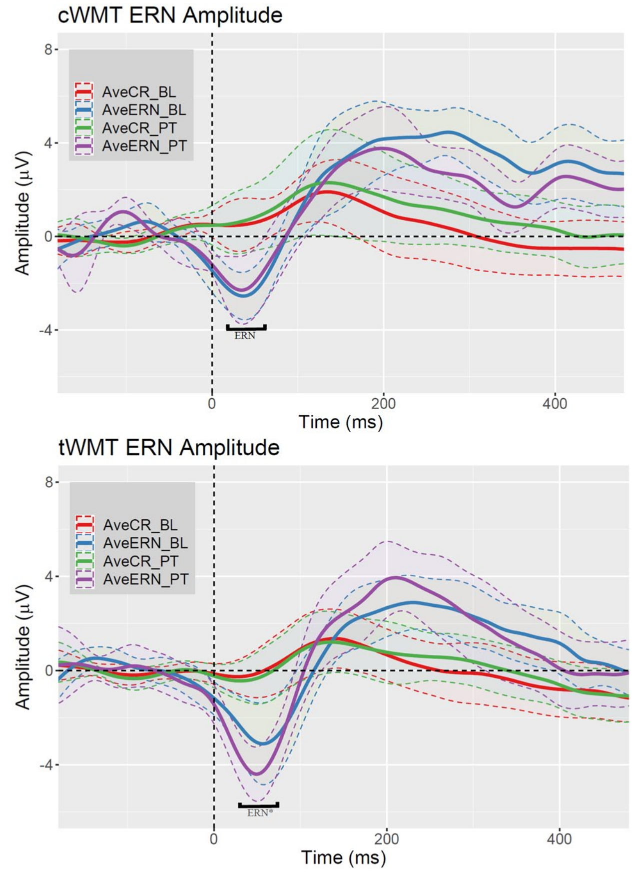

Fig. 6 Grand Average Waveforms from Error Trials of Flanker Task across Time for cWMT (**a**) and tWMT (**b**). The ERP plot was obtained for the error trials of the Flanker task on the ERN component emerging at approximately 30–70 ms post-response at the central region (Cz), across both BL and PT phases. Dashed, shaded areas are representing confidence intervals. *AveCR_BL* averaged correct responses at BL, *AveERN_BL* averaged error responses at BL, *AveCR_PT* averaged correct responses at PT, *AveERN_PT* averaged error responses at PT. Asterisk indicates $p = 0.0506$

Discussion

This study examined the effect of an emotional adaptive dual n-back training program on neurocognitive indices of WM functioning and emotional symptoms among high-trait anxious individuals. Consistent with our first hypothesis, we observed that tWMT compared to cWMT showed a greater improvement in WMT Gain Index at the end of nine training sessions. This result is in line with previous studies showing that high-potency adaptive dual n-back training generated better outcomes than low-potency non-adaptive 1-back training (Larsen et al. 2019; Owens et al. 2013; Sari et al. 2016). Additionally, we found both emotional training regimens improved the untrained WM performance (i.e., ACST). No group showed a transfer effect to reading span task, which is consistent with previous studies using neutral adaptive n-back training (Jaeggi et al. 2008, 2010). There was a significant transfer effect on the operation span task at PT and 1-month FU for both training groups. However, only tWMT led to a meaningful transfer gain on the spatial span task after the training. Given that the 1-back training also required practice on a WM task, it is possible that cWMT

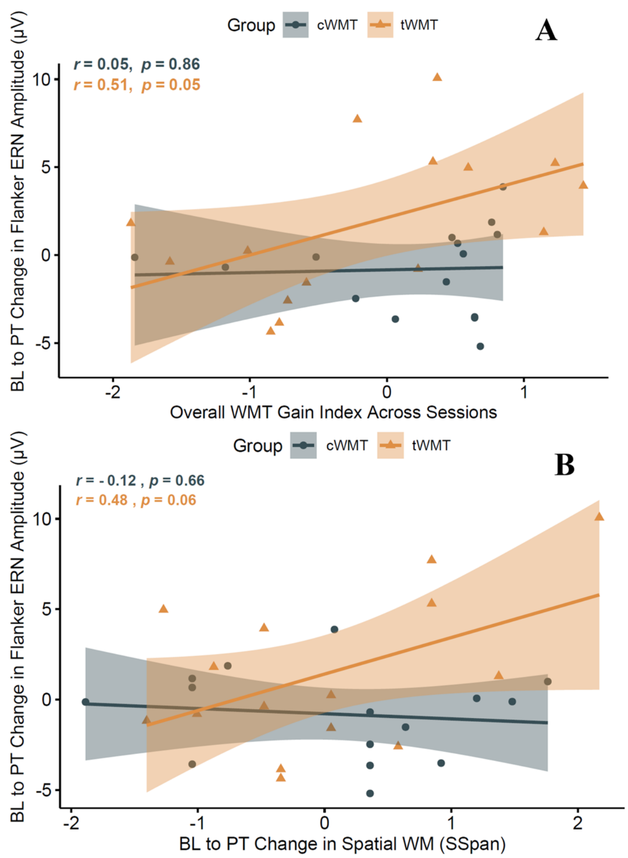

Fig. 7 Association between Magnified ERN amplitude (Flanker) with Improved WMT Gain Index (**a**) and Spatial WM (SSpan; **b**) for tWMT and cWMT. The orange line shows a strong correlation between the BL-to-PT change scores on the ERN amplitude (larger value shows a larger magnified ERN) with *the WMT gain index* (**a**; standardized: larger values indicates larger WMT gain throughout the training) and the BL-to-PT change scores on SSpan (**b**; a larger value indicates a larger spatial WM improvement) for tWMT. No such a pattern was observed for cWMT. Shaded area represents confidence intervals

also delivered effective training ingredients (e.g., training of selective attentional control) which led to significant transfer effects. It is also possible that this result might be due to demand and practice effects or non-specific training effects (Leone de Voogd et al. 2016), although this is unlikely because only tWMT promptly achieved a large transfer effect to spatial span at PT. Additionally, this result was substantiated by the large correlation found between gains obtained for spatial span and ERN amplitude after the training only for tWMT. Overall, it appeared that cWMT yielded unanticipated training effects, as the emotional 1-back training might have affected short-term storage capacity at visual (OSpan) or spatial (SSpan) domains.

We consistently observed that both training conditions generated meaningful gains in filtering efficiency capacity at PT and 1-month FU. Similarly, Owens et al. (2013) found that tWMT led to improvement in WM capacity and neural filtering efficiency measured by a non-emotional Change Detection task, while cWMT did not show such improvement. Here we used an emotional version of the Change Detection Task (Stout et al. 2015) and observed filtering efficiency at the behavioral level, and both trainings also included affective stimuli. It appeared cWMT had some unexpected potency. In fact, this emotional 1-back task required subjects to actively maintain two streams (visual and auditory) of affective information. This demanded increased engagement of selective attentional allocation to sufficiently maintain targets until subsequent trials while disregarding irrelevant stimuli. Thus, this training might have offered opportunities to practice selective attention and inhibitory abilities of WM, which in turn resulted in increased filtering of irrelevant fearful stimuli (Leone de Voogd et al. 2016). In fact, we observed a medium-to-large association for cWMT and a large association for tWMT between the change detection task accuracy gain from BL to PT and the WMT Gain Index. This indicated larger training gains are associated with larger CDT accuracy performance following the training. However, we did not examine whether such a gain was achieved at a neural level. Nevertheless, it is of particular note that both training regimens significantly impacted on the CDT condition with fear distractors (NTFD), but not target-only conditions (NT1 and NTFT). Thus, it appears that emotional n-back training can specifically improve the filtering of emotionally salient distractors.

Per our third hypothesis, we found that both trainings brought about significant gains to attentional executive domains at the behavioral and neurocognitive levels, as observed by improved accuracy and RT, and larger N2 and ERN amplitudes at PT. The behavioral results were also maintained for 1-month FU. Studies reported transfer effects of non-emotional n-back trainings to tasks of attentional control in a sample of high-trait anxious individuals (Sari et al. 2016), healthy (Covey et al. 2019), and individuals with multiple sclerosis (Covey et al. 2018), as well as transfers to an "electrophysiological measure of trait attentional control" (Sari et al. 2016). Schweizer et al. (2017) found a 20-session of an emotional n-back training led to considerable improvements in RT and commission errors of a Go/NoGo task in a sample of adolescents with PTSD. Consistent with our ERP finding, Covey et al. (2018, 2019) also reported increased N2 amplitude after 20 sessions of n-back training for healthy and clinical samples accompanied with an enhanced attention control performance. Interestingly, we found a significant positive correlation between the RT improvement at PT and corresponding N2 amplitude increased for both training groups. Alluding to non-specific training effects, this coordinated behavioral and neural data strengthened the idea that both training programs had substantial transfer effects to attentional domain. However, we believe this matter requires further explanation. We found that only tWMT showed a large increase in ERN amplitude after the training. Although the result was not significant ($p = 0.051$) with a large effect size, it appeared tWMT was more potent to impact on underlying cognitive processes which went beyond early-stage, quick attentional allocation, and benefited higher order monitoring and updating system of WM (Cavanagh and Shackman 2015; Wilkowski and Robinson 2016). Horowitz-Kraus and Breznitz (2008) found ERN amplitude was reduced when WM load was high. In a subsequent study, Horowitz-Kraus and Breznitz (2009) provided evidence that WM capacity was positively associated with the ERN amplitude, reporting increased ERN amplitude following a cognitive training. Indeed, our ERN results dovetail with the result reported by Horowitz-Kraus and Breznitz (2009). In the absence of such an association for cWMT, the increased ERN amplitude after the training was strongly associated with the WM training gains observed only for tWMT. The increased ERN magnitude may reflect an enhanced representation of conflict, which is associated with improved WM functioning (i.e., monitoring and updating) and better execution of attention in subsequent trials (Horowitz-Kraus and Breznitz 2009; Wilkowski and Robinson 2016).

Now it begs the question whether these changes observed at the neurocognitive level led to any meaningful decline in trait anxiety and worry symptoms. Consistent with our ERN result, we found that only tWMT showed significant reduction in worry symptom and trait anxiety after the training, however, at 1-month FU both groups demonstrated significant decline in both symptomologies. Although this symptom reduction was statistically significant following the training and at 1-month FU, we failed to obtain a clinically meaningful improvement based on the measure scales (e.g. > 8.5 for PSWQ; Beck et al. 1995). However, it is possible that an extended schedule of training (e.g., 20 sessions or more) would have resulted in greater symptom reduction. In fact, Schweizer et al. (2017) reported that a 20-session of emotional n-back training yielded significant improvement in PTSD symptom in an adolescent sample. Larsen et al. (2019) also reported clinically meaningful reduction in PTSD symptom severity (a hallmark of anxiety symptomology) for a sample of veterans who completed 15 sessions of emotional n-back and 1-back trainings. It was also encouraging to find an overall medium-to-large strength of association between progressed achieved through the tWMT and the worry symptom reduction. Numerous studies showed direct association between greater WM performance and lower worry self-reports (Hallion et al. 2014; Hayes et al. 2008; Stout et al. 2015). Accordingly, this finding provides a clue that emotional WMT improvement might be related to the change in worry symptom.[2]

We believe there are merits in discussing the relationship between improved WM performance and ERN amplitudes in regards to reduced emotional symptoms. Noticeably, it is well-documented that cognitive control plays a significant role in emotional regulation (Ochsner and Gross 2005). Researchers have suggested error monitoring contributes heavily to goal-directed behaviors (Carver and Scheier 2012). Additionally, numerous studies have reported robust ERN amplitudes and corresponding post-error RT slowing are positively associated with self-regulation benefits, including greater down-regulation of anxious reactions to daily stressors (Compton et al. 2008), lower aggression (Chang et al. 2010), and lower externalizing problems (Hall et al. 2007). Robinson et al. (2010) reported that enhanced error monitoring was beneficial in reducing negative affect among individuals with elevated neuroticism, reporting that a better attentional re-adjustment after detecting an error is predictive of positive mood. Wilkowski and Robinson (2016) suggested that better error monitoring "may lead to greater emotional well-being."

Together, given our consistent results of transferred effects occurring in cognitive and emotional domains, we believe our results corroborate the current literature by showing that a moderate schedule of an emotional adaptive n-back training might be more effective than an emotional non-adaptive 1-back training in producing sizable gains in neurocognitive and emotional processes associated with WM. Despite our findings, we should point out the limitations of this study. First, we found that even an emotional 1-back training yielded unexpected training effects to generate transferable gains to worry symptom reduction. Thus, the WM training research needs to utilize a compatible but non-effective training program as a control condition for better assessing WM training effects. Second, this study is limited in terms of a small, non-diverse sample. Although our sample size was relatively smaller than the previously reported studies using similar procedures (Jaeggi et al. 2014), it was encouraging to observe sizable improvement in WM processes, and anxiety and worry symptom. Third, we cannot rule out the possibility that the observed training effects could be attributed to non-specific factors (e.g., spontaneous recovery, attention from the researchers), as both groups received a similar form of WM training (without a no-training comparison group). Future studies should consider a waitlist control, as well as a more stringent

[2] It appears that WMT produced a negligible change in the level of trait anxiety. Trait anxiety is a broader and more dispositional vulnerability to experience anxiety symptoms across a wide range of contexts (Eysenck 1987; Girdron 2013). Thus, it is possible that trait anxiety may not be directly relevant as an immediate training outcome for short-term WMT, and it requires more intensive training (Sari et al. 2016).

comparison groups (e.g., a credible placebo intervention, or an established intervention for anxiety disorders such as cognitive behavioral therapy) to rigorously examine the potential effects of computerized WM training for anxiety disorders. Lastly, the ERP data were averaged across the congruent and incongruent trials, as N2 amplitudes were equivalent between the two trial types. There may be a few reasons why we did not observe larger N2 amplitudes in incongruent trials or their differential changes between the two trial types over training. First, it may be that the current emotional WM training was not potent enough to specifically improve the ability to control cognitive interference imposed by incongruent trials. Second, considering the lack of difference in N2 amplitudes between the two trial types *at pre-training*, it is possible that the equivalent proportion of congruent vs. incongruent trials (i.e., 50% vs. 50%) may have attenuated the interference demand of the incongruent trials. Relatedly, there is evidence that the heightened frequency of conflict/incongruent trials can diminish corresponding the fronto-central N2 amplitude (Purmann et al. 2011). Thus, the N2 component in our Flanker task is likely to reflect more general early-stage attentional control processes, rather than specifically tapping on cognitive interference control.

Overall, we believe this study was significant and innovative in several regards. First, this was one of the few studies to examine the underlying neurocognitive mechanism of emotional WM training in the context of a randomized controlled trial. Second, it encourages designing new studies to examine the effect of WMT to develop an effective cognitive intervention for anxious individuals to improve their ability to filter out irrelevant threatening thoughts or images. Third, successful outcome may guide the development of a potentially standalone or adjunctive cognitive intervention that is accessible and cost-efficient with a strong scientific rationale and empirical evidence.

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Compliance with Ethical Standards

Conflict of Interest Salahadin Lotfi, Richard T. Ward, Maryam Ayazi, Ken P. Bennett, Christine L. Larson, and Han-Joo Lee declare that they have no conflict of interest.

Ethical Approval This study has been conducted following the principles of ethical and professional conduct, under the approval of IRB at the University of Wisconsin-Milwaukee as a human subject research project.

Informed Consent Participants voluntarily provided informed consent to participate in the current study.

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