**Supplemental Material**

**Baseline Cognitive Control Performance**

Prior to group assignment, all participants completed a baseline assessment. This served to familiarize participants with some task procedures prior to study onset, and to help rule out pre-existing group differences. To index baseline performance in inhibitory control, participants completed a resource-demanding vigilance task—the Response Inhibition Task (RIT; MacLean et al., 2009). In the RIT, participants are asked to discriminate between rare target and frequent non-target stimuli over the course of 32 minutes. Participants responded to commonly occurring non-target (long line) stimuli while withholding behavioral responses to rare target (short line) stimuli.

Response inhibition accuracy was quantified using the non-parametric index of perceptual sensitivity, *A* (Zhang & Mueller, 2005), where hits are defined as correct inhibitions to targets and false alarms as incorrect inhibitions to non-targets. *A* ranges from 0 to 1, with 0.5 indicating chance performance and 1 perfect performance. For each participant, reaction time variability was quantified as the reaction time coefficient of variability (RTCV = standard deviation RT / mean RT) for non-target trials (864 trials). Lower RTCV values indicate lower reaction time variability.

There were no group differences in performance accuracy or RTCV at the baseline assessment. The mean accuracy for the training first group was 0.90 (*SD* = 0.072) and for the waitlist control group was 0.90 (*SD* = 0.062), *t*(58) = 0.000, *p* = 1.000, *d* = 0.00. The mean RTCV for the training first group was 0.31 (*SD* = 0.084), and for the waitlist control group was 0.30 (*SD* = 0.086), *t*(58) = 0.456, *p* = .650, *d* = 0.12. Thus, there were no significant differences in performance on this cognitive control task between groups prior to random assignment. Importantly, we have shown that the RIT is sensitive to subsequent meditation training in this same cohort of participants (Sahdra et al., 2011; Zanesco, King, MacLean, & Saron, 2018).

**Fitting the Computational Model**

The model was fit to trial-level data using cumulative density functions (CDFs), which capture response time distributions (.1, .3, .5, .7, .9 quantiles); and conditional accuracy functions (CAFs), which describe error proportions in five equally spaced response time bins. CAFs represent the error in the data that is considered in the fitting procedure (Servant et al., 2016; White et al., 2018). Parameters were constrained to be positive numbers (and in the case of *a* and *b*, greater than or equal to 1).Following work on the parameter recovery of this model (White et al., 2018), the observed and predicted CDFs and CAFs were fit by minimizing the following χ2 statistic:

where and represent the observed and predicted proportion of trials, respectively, in bin *j* of trial type *i* (i.e., congruent or incongruent trials); and *Ni* represents the number of trials per trial type *i*. We fit the model using the subplex optimization method (Rowan, 1990), which divides the parameter space into subspaces and then optimizes these subspaces by the Nelder-Mead simplex method. The subplex optimization method is better suited for optimization problems involving numerous parameters, dismissal of unacceptable parameters (e.g., parameters with negative values), and noisy data (i.e., models with random sampling, such as a Wiener diffusion process)—making this optimization method more appropriate for the present model than the simplex method (Farrell and Lewandowsky, 2018).

Parameter estimates were obtained for each participant according to the following procedure. First, to determine plausible starting values, we selected the best fitting parameters from prior work that fit this model to flanker data (Ulrich et al., 2015). We then compared the observed and predicted means and standard deviations from 10,000 simulated trials to gross behavioral outcomes on the flanker task (e.g., mean congruent and incongruent response times and error rates), averaged across all participants, and adjusted the parameters to better match the gross behavioral metrics. Next, we used these parameters to randomly generate 14 sets of additional parameters (for 15 total sets) that were constrained to be greater than zero and normally distributed around each respective initial parameter value, with a variance of 50% of the initial parameter value. These 15 parameter sets were then fit to the data from each participant group (training first vs. waitlist control) by simulating 10,000 trials of each type (i.e., congruent and incongruent, for 20,000 total trials) and comparing the observed and predicted CDFs and CAFs using the procedure described in the preceding paragraph. The final parameter values from the best-fitting model were then selected as the best-fitting parameters for the respective participant groups.

Once the best-fitting parameters for each group were found, they were used as starting values to randomly generate nine sets of additional parameters (for ten total sets) for each participant in each group. Again, the parameters were constrained to be greater than zero and normally distributed around each respective initial parameter value with a variance of 50%. The resultant parameter sets were then fit sequentially to each participant’s data by simulating 10,000 trials of each type (i.e., congruent and incongruent; 20,000 total trials) and comparing the observed and predicted CDFs and CAFs. Values from the best-fitting model were selected as the best-fitting parameters for each participant, and used in statistical analyses.

**Relationship between Controlled and Automatic Attention**

An astute reader may wonder about how dissociable controlled attention and automatic attentional activation are in fitted data, and whether overlap between these attentional components might explain the inconsistent effects of meditation on automatic attentional activation between retreats. Within the formal model, these parameters are independent and exert different effects within the model. However, estimated data, which are subject to local minima, may result in correlations between any estimated parameters. The parameters are considered independent and estimated as such within the model, and to our knowledge no work has examined potential correlations between the controlled and automatic attentional parameters. To address this question, we calculated correlations between these parameters in Retreat 1 of the current dataset (*n* = 60), as well as in a novel analysis of another dataset collected by this study’s first author (Shields et al., 2019; *n* = 107).

In the current dataset, there was a positive correlation between controlled attention and automatic attentional activation, *r*(58) = .285, *p* = .027, when collapsing across active training participants and waitlist controls; in the second dataset, however, there was a nonsignificant negative correlation between controlled attention and automatic attentional activation, *r*(105) = -.147, *p* = .132. We believe this discrepancy in correlations between parameters across studies may be because shamatha meditation training enhances both controlled and automatic attention. That is, the meditation intervention may lead to increases in both controlled and automatic attention, leading to a correlation between these parameters when collapsing across the training and control groups. In this scenario, the correlation would be epiphenomenal to the effects of the intervention on both of these parameters. In contrast, absent an intervention that influences these parameters, they are uncorrelated and even nonsignificantly negatively correlated, as is seen in the second dataset. In line with this possibility, when the Retreat 1 training and waitlist control groups were examined separately, correlations between controlled attention and automatic attentional activation in the were nonsignificant in both groups, *p*s > .22. In addition, the effects of shamatha meditation training on automatic and on controlled attention when controlling for the other (i.e., when automatic attention is used as a covariate with controlled attention as the outcome, or vice versa), remain very close in magnitude (controlled attention *d* = 0.52; automatic attention *d* = 0.41) to when no covariate is included (controlled attention *d* = 0.64; automatic attention *d* = 0.56). Therefore, the effect of shamatha meditation on automatic attentional activation does not appear to be driven by the effects of shamatha meditation on controlled attention, and vice versa.

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