Supplemental Material

1. Formal Relation between Alertness and VPS in TVA: Predictive Influences on Attention and the Model of Components of Attentional Bias

TVA proposes that visual representations are in a biased competition for access to a limited visual short-term memory (vSTM) store. During the race for encoding, objects receiving higher attentional weighting are processed faster and encoded first until the store is filled. When an object is presented alone, its encoding speed $v(x, i)$, i.e., the rate at which the categorization "object x belongs to category i" is made, is given by

$$v(x,i) = \eta(x,i)\beta_i,$$

Where $\eta(x, i)$ is the strength of sensory evidence that x belongs to category i and β_i is the observer's bias towards category i. The bias at a given moment is proposed to be determined by three multiplicative components (Bundesen et al., 2015):

$$\beta_i = Ap_iu_i$$

where A reflects the level of alertness, probability p_i reflects the expectancy of, and utility u_i the subjective importance of particular objects. The parameter reflecting total visual processing speed C of a given observer is defined as the sum of all v values. In multi-element displays containing targets of equal relevance to the observer, such as in whole-report displays, C can be assumed to be directly proportional to v. Thus, variation in alertness should directly translate into proportional changes in parameter C.

2. Reasons for Exclusion

2.1 Study 1

Alertness-training group: longer sickness (1), technical issues (1); *active-control group*: personal issues (1); *passive-control group*: personal issues (4).

2.2 Study 2

Personal distress (2), neurodegeneration signs in brain scan (1), cerebral hemorrhage (1), psychiatric disorder symptoms (1), technical issues (4), *drop-out* due to personal reasons (2).

3. Alertness-Training and Active-Control Tasks

Tasks ran on PCs with 19-inch monitors (resolution 1280 × 1024 pixels; 60-Hz refresh rate). Sessions ended after 45 minutes.

3.1 Alertness Training

Headphones isolated participants from noise and presented them with driving and braking sounds. In the first session, participants underwent practice with feedback on their reactions. After three consecutive correct reactions, the actual training started. For each level, the criterion for timely responses was pre-set: 1.8 and 0.3 sec for the lowest and highest levels, respectively. The training started at the lowest level, and this was adjusted after five timely reactions, by calculating the mean reaction time by 0.55 SDs and introducing this as the appropriate difficulty level (potentially skipping intermediate levels). Thereafter, every ten successive reactions, the level was adjusted anew based on the percentage of responses that met the criterion (if <50%, the level decreased; if 50–80%, it stayed the same; if >80%, it increased).

3.2 Active-Control Task

Each block consisted of 20+n trials and lasted about one minute; blocks contained 6 targets and 14+n distractors at 1 out of 8 possible locations. After each block, feedback was provided. The training started at 1-back level. If 75–85% of reactions were correct, the level was maintained; if it was above, *n* was increased by 1; if it was below, *n* was reduced by 1 (except for *n*-back level 1). Misses and false alarms were counted as errors.

Table S1. Pearson correlations between modeled and observed whole-report data: Goodness-of-Fit (GOF) mean ± SD values.

	GOF *pre*	**GOF *post***	***t*-test *pre* vs. *post***
Study 1			
Alertness Training	.936 ± .030	.875 ± .214	$t(24) = 1.40$, $p = .17$
Active Control	.932 ± .027	.942 ± .022	$t(24) = -1.78$, $p = .09$
Passive Control	.934 ± .082	.946 ± .043	$t(24) = -.86$, $p = .40$
Study 2			
Alertness Training	.971 ± .032	.965 ± .027	$t(28) = 1.08$, $p = .29$

4. Whole- and Partial-Report Assessment

4.1 Study 1

In whole-report, the ‘intermediate’ exposure duration was the individual time needed to report one letter correctly. This was combined with a shorter (half) and a longer (double the intermediate) exposure duration.

In partial-report, the individual exposure durations were set such that about 80% of single targets and at least 60% of dual targets could be reported correctly. Dual stimuli were arranged vertically or horizontally.

The experiments were run on PCs with 17-inch monitors, with black screen background (resolution 1024 × 768 pixels; 75-Hz refresh rate; viewing distance 60 cm, controlled by chin rest), in a dimly lit room (different from the training room).

4.2 Study 2

Study 2 employed updated TVA paradigms (Gögler et al., 2017) with minor changes: a fixation circle and slightly larger (1.3° of visual angle) red or blue letters; in whole-report: equidistant letters around the fixation marker and seven (not six) 'effective' exposure durations, and data analysis with LibTVA script (Dyrholm, 2012).

5. fMRI Data Analysis

5.1 Acquisition

MRI data were acquired in the 'Klinikum rechts der Isar' of the Technische Universität München. Foam padding was used to constrain participants' head motion during scanning; earplugs and headphones were provided to reduce noise. Six-hundred volumes of BOLD-fMRI signal were acquired using a multiband EPI sequence (SENSE factor = 2, M-factor = 2).

5.2 Preprocessing

Rs-fMRI volumes were preprocessed (Chao-Gan & Yu-Feng, 2010) for each participant. The first five volumes were discarded. Data were normalized to MNI space using DARTEL (Ashburner, 2007) with a 2-mm isotropic voxel size and smoothed using a 4-mm full-width-at-half-maximum Gaussian kernel. Nuisance covariates regressed out were the six head motion parameters and their first temporal derivatives; the signal averaged over white matter, lateral ventricles, and whole brain; and 'bad' time points (i.e., framewise displacement > .5 mm and 1 backward and 2 forward adjacent time points; Power et al., 2012).

5.3 Network Selection

We cross-correlated our 20 group spatial maps resulting from ICA (Smith et al., 2004) and dual regression (Beckmann et al., 2009) with reported resting-state network templates (Yeo et al., 2011), using FSL's *fslcc* command, and selected spatial maps correlating highest with the networks of interest as resting-state networks for further group analyses. We identified one cingulo-opercular network (r = .39 with Yeo_8), our network of interest. To control for specificity of results, we identified three control networks relevant for visual attention, the visual (r = .61 with Yeo_1) and dorsal-attention (r = .42 with Yeo_6) networks, and one relevant for aging, the default-mode (r = .36 with Yeo_17) network. We used an additional set of resting-state network templates based on ICA (i.e., Allen et al., 2011) to identify the right frontoparietal network (r = .60 with Allen et al.'s IC60).

5.4 Prediction of VPS from functional connectivity

Reliable effect size estimates of the cingulo-opercular network's functional connectivity (CON-FC) predictiveness should be obtained from independent samples. Nevertheless, to allow informing future research (e.g., for a priori power calculations), we computed an effect size (R^2) of the CON-FC in the identified cluster (i.e., medial superior frontal gyrus) for the prediction of VPS changes. Based on a linear regression of VPS change on the CON-FC cluster, we found an R^2 of .45 ($F_{(1,27)} = 24.19$, $p < .0001$), indicating a strong effect (corresponding Pearson's $r = .69$ or Cohen's $f^2 = .82$).

6. References

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