Neural efficiency in working memory tasks: The impact of task demand and training

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Abstract

Studies of human intelligence provide strong evidence for the neural efficiency hypothesis: More efficient brain functioning in more intelligent individuals, that is, less cortical activation in brighter individuals.

The main goal of this study was to explore the relationship between intelligence and cortical activation in combination with a cognitive training. In 83 participants, cortical activation was assessed by means of event-related desynchronization (ERD) before and after working memory (WM) training. In a pre-test training post-test design, ERD during performance of trained as well as untrained transfer tasks was correlated with scores in a psychometric intelligence test (Raven's Advanced Progressive Matrices test).

We found a negative correlation between ERD and intelligence for moderately difficult tasks. A decrease in cortical investment from pre- to post-test was found for simple tasks but likewise for individuals with lower and higher intelligence. We could not find a stronger activation decrease from pre- to post-test for individuals with higher intelligence. These findings suggest partial confirmation of the neural efficiency hypothesis for moderately difficult tasks and they provide an indication that training can help in reducing cortical activation while solving simple tasks.

Keywords: working memory; intelligence; neural efficiency; training; event-related desynchronisation (ERD)

Theoretical Background

According to the neural efficiency hypothesis, more intelligent individuals can be characterized by less brain activation than less intelligent individuals (Haier et al., 1988). This original hypothesis of neural efficiency was introduced by a PET study showing less brain glucose metabolism in more intelligent individuals while solving cognitive tasks. Haier and colleagues stated: "Intelligence is not a function of how hard the brain works but rather how efficiently it works. … This efficiency may derive from the disuse of many brain areas irrelevant for good task performance as well as the more focused use of specific task-relevant areas" (Haier, Siegel, Tang, Abel, & Buchsbaum, 1992b, pp. 415–416). By using EEG measurements during cognitive task performance, the hypothesis has been repeatedly confirmed. In particular, it has been shown that event- related desynchronization (ERD) in the upper alpha band, reflecting a measure of general cortical activation, is negatively related to intelligence (Pfurtscheller & Aranibar, 1977, Klimesch, Doppelmayr, & Hanslmayr, 2006; Klimesch, Doppelmayr, Pachinger, & Ripper, 1997) However, the body of evidence is not entirely consistent. Recent findings suggest a more differentiated picture of the validity of the neural efficiency hypothesis. They point out the modulating role of task complexity, practice, learning and expertise as well as gender, and the importance of an adequate intelligence measure (Neubauer, Grabner, Fink, & Neuper, 2005; Neubauer & Fink, 2003). The relation between neurophysiological activity and intelligence – predominantly for fluid intelligence– arises for a variety of tasks of subjective low to moderate task difficulty.

Most studies referring to the neural efficiency hypothesis apply intelligence tests while measuring cognitive activation (see Neubauer & Fink, 2009). Other studies that tried to broaden the validity of the hypothesis found similar relations between intelligence and cortical activation in WM tasks (Grabner, Fink, Stipacek, Neuper, & Neubauer, 2004; Rypma & D'Esposito, 1999).

Only few studies so far investigated the influence of task training on the relation between neural activation and intelligence. The neural efficiency hypothesis was supported in two studies that found stronger activation decrease after training for individuals with higher intelligence (Haier et al., 1992b; Neubauer, Grabner, Freudenthaler, Beckmann, & Guthke, 2004). In the study by Neubauer et al. (2004), this result was found for tasks of high difficulty.

Summing up, for moderate untrained and difficult trained tasks support for the neural efficiency hypothesis could be found. However, it is still unclear in which way the relation between neural activation and intelligence is influenced by training and if possible training effects on neural efficiency can be found on tasks of different difficulty.

The present study tries to answer the question if intensive cognitive training can alter the relation between cortical activation and intelligence in different tasks. The applied training had the aim to enhance WM capacity. Besides investigating changes concerning trained tasks, we also look at transfer effects to related but untrained tasks. Results on the trainability of WM are still heterogeneous (for a review see Shipstead, Redick, & Engle, 2012; Chein, & Morrison, 2010). Although there are various newer studies with positive behavioral results concerning trainability of WM, there are also many studies with negative results (for a meta-analysis see Melby-Lervåg & Hulme, C., 2013). It remains unknown which characteristics of a WM training influence its effectiveness (Shipstead, Redick, & Engle, 2010). In order to add evidence to this open question, in the present study we administer three different training paradigms varying in the amount of WM load during training and differing in demands for interference resolution.

The principal aim of the present study is to analyze neural correlates of cognitive performance by means of ERD before and after WM training. It is expected that (a) concerning the neural efficiency hypotheses, more intelligent individuals should show less cortical activation while solving WM tasks than less intelligent individuals, (b) training will alter this relationship, and (c) training-induced changes of cortical activation are related to individuals' intelligence level.

Method

Participants

A total of 83 healthy students of science- and humanities-related fields from three Swiss universities completed the study (M_{age} = 23.7, SD = 3.3, 36 males, 47 females). Eight participants dropped out due to installation problems of the training software on their home computer (5 participants) or due to non-adherence to the training paradigms or sessions at the institute (3 participants). All participants were right-handed and without any medical or psychological diseases (both determined by self-). The participants were paid for their participation in the study.

Procedure

In an independent group design, participants were randomly assigned to one of three groups differing in WM-load during training: (a) A low-WM-load-group trained three different tasks with low WM load, (b) a medium-WM-load-group trained three different non-adaptive tasks with moderate WM load and a large amount of interference trials (c) a high-WM-load-group trained an adaptive dual n-back task with high WM load and a large amount of interference trials (similar to Jaeggi et al., 2008). All groups trained 5 days a week during a 3-week period for half an hour daily on their home computer. To check the plausibility of training gains, the first and last training sessions took place at the first author's institution and were performed together with transfer tasks.

Before and after training, an assessment session took place at the first author's institution. Participants were asked to solve WM tasks (training and transfer) and a mental arithmetic task while EEG was recorded. Furthermore, they completed an intelligence test (Advanced Progressive Matrices Test, APM; Raven 1990). The session before training served to assess baseline performance and the session after training aimed to assess possible transfer from WM training. The three groups did not differ in their initial intelligence level and their initial performance in the training and transfer tasks.

EEG

EEG measures were conducted by an ActiveTwo-System of BioSemi (BioSemi, Amsterdam, The Netherlands). Event-related desynchronization/synchronization (ERD/ERS) was calculated for the upper alpha band (10–13 Hz) (Klimesch, 1999; Neubauer, Fink & Grabner, 2006). For a detailed description of data analyses see Grabner and De Smedt (2011) and De Smedt, Grabner und Studer (2009). Negative values (ERD) indicate desynchronisation and a decrease in power. Positive values (ERS) indicate synchronisation and an increase in the power. For statistical analyses, a global measure of cognitive activation was formed by averaging all 64.

Material

Training

The high-WM-load-group trained one task for the entire 30 minutes. It was an adaptive and dual version of the n-back task that placed high WM load due to a large amount of interference trials (Dual-N-back; similar to Jaeggi et al., 2008). In this group the average n-back level was assessed. The medium-WM-load-group trained three non-adaptive WM tasks: A three-back task with letters (3back), a face recognition task (4Faces, see figure 1), and a letter recognition task (4Letters). These tasks were characterized by moderate WM load with a focus on resolution of proactive interference in WM. Solution time and solution rate was measured. The low-WM-load-group trained similar tasks as the medium-WM-load group, but tasks had lower WM load (i.e. only 1 item for all 3 tasks: 1back, 1Letter and 1Face). Solution time and solution rate was measured.

Tasks to assess transfer

As a fluid intelligence test, the well-established Advanced Progressive Matrices Test (APM, Set II) by Raven (1990) was administered. As all participants solved the APM twice, once at pre-testing before and once after training, an even-odd split version was presented (participants were randomly assigned to the specific order). As only half the items were presented at each time point, no IQ-value could be calculated, (raw values pre-testing M = 12.47, SD = 2.52). Two groups were formed by a median split of the raw values at pre-testing (lower intelligence-group: n = 40, M = 10.32, SD = 1.44; higher intelligence-group: n = 43, M = 14.47 SD = 1.40). The two groups differed significantly in their achieved values ($t(81)$ = 13.265, p < .001; d = 0.49).

Three transfer tasks were administered: Two WM tasks representing two different subcomponents of WM and a mathematical task. In a task-switching task (Task-Switch) participants had to either decide whether the value of a three digit number was below or above 500, or whether the number was even or odd. In a monitoring task (Monitoring) participants had to detect changes in a grid of nine three-digit-numbers and react on constellations of same final digits. The transfer task of the mathematical domain was a mental arithmetic task with subtractions of two digit numbers with carries (Mental Arithmetics, see figure 2).

Furthermore, the subjective cognitive demand of a task was measured by the mental effort rating scale (Paas, 1992; Paas, Tuovinen, Tabbers, & Van Gerven, 2003). This allowed us to measure cognitive task demands in more subjective (mental effort) and objective (ERD) manner and compare them.

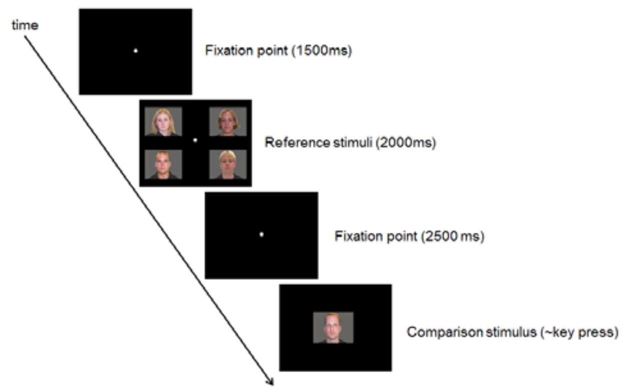

Fig.1. Schematic display of an example item of the 4Faces training task

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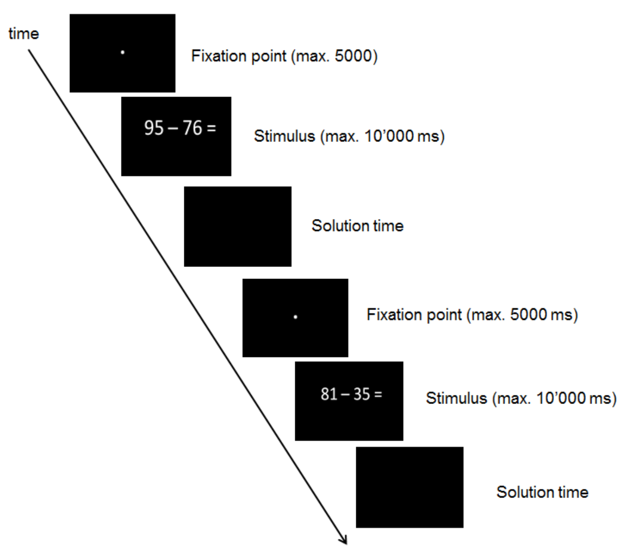

Fig.2. Schematic display of an example item of the transfer task Mental Arithmetics

Results

For all analyses only data of correctly answered test items were considered.

Overall gains from pre- to post-testing were similar for all tasks and no group differences occurred (see table 1). Therefore, the total of 83 participants was grouped into two groups according to their performance in the APM, irrespective of the training group.

To compare the two intelligence-groups on their behavioral performance a repeated measure ANOVA (within-subject factor time and between-subject factor intelligence-group)[1] was performed for each transfer task separately. All tasks showed main effects of time whereas neither a main effect of intelligence-group nor an interaction between intelligence-group and time were found. So behaviorally, no intelligence differences were found – all participants increased performance (solution time and except of ceiling effects in very easy tasks: 1letter, 1face, 1back and 4letters also for solution rates) from pre- to post-testing irrespective of their intelligence level.

To investigate differences in cortical activation – quantified by the ERD in the upper alpha band – for all tasks we computed separate repeated measures ANOVAs with intelligence-group (lower vs. higher intelligence) as a between-subject variable and time (pre- vs. post-testing) as a within-subject variable. Differences in cortical activation between the intelligence-groups (reflected in a main effect intelligence-group) occurred in two tasks: the transfer task Mental Arithmetics and the training task 4Faces (see table 2 & 3). For both tasks individuals with higher intelligence showed less cognitive activation. This supports the neural efficiency hypothesis. However, these activation differences between the intelligence-groups did not change by training and remained from pre- to post-testing.

Differences in cortical activation between pre- and post-testing (reflected in in main effects of time) were found for the two training tasks 1Face and 1Letter (see table 3). The main effect intelligence-group as well as interactions between time and intelligence-group did not reach statistical significance. Participants – disregarding of their intelligence – showed less cortical activation after training than they did before training. For cortical activation we did not find interaction effects between the intelligence-group and time for any of the tasks. In addition, there were no performance differences between intelligence levels in solution time and solution rate. This indicates that no performance-neural activation trade-off can be made responsible for the result.

According to the mental effort rating scale (possible values between 1 and 10) both tasks with activation differences between the intelligence-groups were of moderate difficulty (values between 5 and 6). Both tasks showing differences between pre- and post-testing in the amount of cognitive activation measured by ERD are rated as simple (values between 3 and 4). A decrease in subjective cognitive effort was found for the 3-back task and the Dual-

[1] All general linear model (GLM) analyses for repeated measures were performed and if required corrected by a Greenhouse–Geisser correction for the violation of the sphericity assumption.

N-back task. For all other tasks no differences were found between subjective mental effort before and after training.

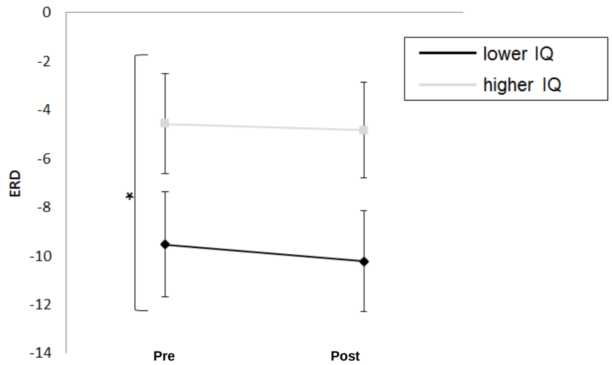

Fig.3. Graph of the main effect group in the Mental Arithmetics task. Error bars represent the standard error of the mean. * = significant main effect group.

Discussion

The main goals of this study were to measure cortical activation while solving WM tasks, to determine whether a negative relationship between intelligence and cortical activation can be found while solving these tasks, to determine effects of practice on cortical activation, and to relate possible effects of practice to participants' intelligence level. For this purpose we conducted a three-week-training of WM tasks with three different WM load levels during training. Behavioral training gains in solution time and solution rate were found for all tasks, which were not affected by the amount of WM load during training.

It was assumed that (a) according to the neural efficiency hypothesis a negative relationships between intelligence and the amount of cortical activation, namely ERD during performance of cognitive tasks can be found, (b) training would alter this relationship, and (c) a possible training-induced change of cortical activation would be related to the individuals' intelligence level. Supportive evidence for (a) was found in two tasks: Mental Arithmetics and 4Faces. Less intelligent individuals had to invest more cortical resources to solve the tasks. This result is in line with studies promoting a differentiated picture of the validity of the neural efficiency hypothesis. Both our tasks were classified as moderately demanding by the mental effort rating scale which is in line with literature emphasizing task complexity as an important modulating factor (see Neubauer & Fink, 2009). For these two tasks the negative relation did not change from pre- to post-testing.

As for part (b) of the hypothesis we also have a partial confirmation: Two tasks showed a development in cortical activation between pre- and post-testing. In the two tasks 1Letter and 1Face, individuals irrespective of their intelligence level showed less cortical activation after the training sessions. Both tasks were judged as simple by the mental effort rating scale. This result is in line with both Haier et al. (1992a) and Neubauer et al. (2004) who reported less cortical activation after training.

Furthermore, contrary to our expectation (c), no training-related development in the cortical activation occurred that was different for the intelligence-groups. We could therefore not replicate the finding of a stronger activation decrease from pre- to post-testing for individuals with higher intelligence. (Haier et al. 1992b, Neubauer et al., 2004)

In sum, a partial confirmation of the neural efficiency hypothesis could be found: Moderately difficulty tasks show intelligence-related differences in cortical activation and that training can – for simple tasks – help to reduce cortical activation.

References

Chein, J. M. & Morrison, A. B. (2010). Expanding the mind's workspace: Training and transfer effects with a complex working memory span task. *Psychonomic Bulletin & Review*, 17(2), 193–199.

De Smedt, B., Grabner, R. H. & Studer, B. (2009). Oscillatory EEG correlates of arithmetic strategy use in addition and subtraction. *Experimental Brain Research*, 195(4), 635–642.

Grabner, R. H. & De Smedt, B. (2011). Neurophysiological evidence for the validity of verbal strategy reports in mental arithmetic. *Biological Psychology*, 87(1), 128–136.

Grabner, R. H., Fink, A., Stipacek, A., Neuper, C. & Neubauer, A. C. (2004). Intelligence and working memory systems: evidence of neural efficiency in alpha band ERD. *Cognitive Brain Research*, 20(2), 212–225.

Haier, R. J., Siegel, B. V., Tang, C., Abel, L. & Buchsbaum, M. S. (1992b). Intelligence and changes in regional cerebral glucose metablic rate following learning. *Intelligence*, 16, 415-426.

Haier, R.J., Siegel, B.V.,MacLachlan, A., Soderling, E., Lottenberg, S., Buchsbaum,M.S. (1992a). Regional glucose metabolic changes after learning a complex visuospatial/motor task: a positron emission tomographic study. *Brain Research*. 570, 134–143.

Haier, R.J., Siegel, B.V., Nuechterlein, K.H., Hazlett, E., Wu, J.C., Paek, J., Browning, H.L., Buchsbaum, M.S., 1988. Cortical glucose metabolic rate correlates of abstract reasoning and attention studied with positron emission tomography. *Intelligence* 12, 199–217.

Jaeggi, S. M., Buschkuehl, M., Jonides, J. & Perrig, W. (2008). Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of Sciences of the United States of America*, 105(19), 6829–6833.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Research Reviews*, 29(2-3), 169-195.

Klimesch, W., Doppelmayr, M. & Hanslmayr, S. (2006). Upper alpha ERD and absolute power: their meaning for memory performance. In N. Christa & K. Wolfgang (Eds.), *Progress in brain research: Event-related* *dynamics of brain oscillations* (Vol. 159, pp. 151–165). Amsterdam: Elsevier.

Klimesch, W., Doppelmayr, M., Pachinger, T. & Ripper, B. (1997). Brain oscillations and human memory: EEG correlated in the upper alpha and theta band. *Neuroscience Letters*, 28(238), 8-12.

Melby-Lervåg, M. & Hulme, C. (2013). Is working memory training effective? A metaanalytic review. *Developmental Psychology*, 49(2), 270-291.

Neubauer, A. C. & Fink, A. (2009). Intelligence and neural efficiency: Measures of brain activation versus measures of functional connectivity in the brain. *Intelligence*, 37(2), 223–229.

Neubauer, A. C., Fink, A. & Grabner, R. H. (2006). Sensitivity of alpha band ERD to individual differences in cognition. In C. Neuper & W. Klimesch (Eds.), *Progress in brain research: Event-related dynamics of brain oscillations* (Vol. 159, pp. 167– 178): Elsevier.

Neubauer, A. C., Grabner, R. H., Fink, A. & Neuper, C. (2005). Intelligence and neural efficiency: Further evidence of the influence of task content and sex on the brain– IQ relationship. *Cognitive Brain Research*, 25(1), 217–225.

Neubauer, A. C., Grabner, R. H., Freudenthaler, H. H., Beckmann, J. F. & Guthke, J. (2004). Intelligence and individual differences in becoming neurally efficient. *Acta Psychologica*, 116(1), 55–74.

Neubauer, A. C., & Fink, A. (2003). Fluid intelligence and neural efficiency: effects of task complexity and sex. *Personality and Individual Differences*, 35(4), 811-827.

Pfurtscheller, G. & Aranibar, A. (1977). Event-related cortical desynchronization detected by power measurements of scalp EEG. *Electroencephalography and Clinical Neurophysiology*, 42, 817-826.

Paas, F. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive-load approach. *Journal of Educational Psychology*, 84, 429-434.

Paas, F., Tuovinen, J., Tabbers, H., & Van Gerven, P.W.M. (2003). Cognitive load measurement as a means to advance cognitive load theory. *Educational Psychologist*, 38, 63-71.

Raven, J. C. (1990). *Advanced progressive matrices sets 1 and 2*. Oxford: Oxford Psychologists Press.

Rypma, B., & D'Esposito, M. (1999). The roles of prefrontal brain regions in components of working memory: effects of memory load and individual differences. *Proceedings of the National Academy of Sciences*, 96(11), 6558-6563.

Shipstead, Z., Redick, T. S. & Engle, R. W. (2012). Is working memory training effective? *Psychological Bulletin*, 138(4), 628–654.

Shipstead, Z., Redick, T. S. & Engle, R. W. (2010). Does working memory training generalize? *Psychologica Belgica*, 50(3–4), 245–276.

Appendix

Table 1: The type of training has no influence on the amount of gain from pre- to post testing.
Transfer data on solution time for each task: Reporting main effects and interactions for an ANOVA with the between-subject factor training group (low, medium and high load during training) and the within-subject factor time (pre- and post-test)

Task	Main effect time	Main effect training-group	Interaction time * training-group
Solution time			
Task-Switch	$F(1, 79) = 136.01$ $p < .001$ $\eta^2_p = .63$	*n.s.* $\eta^2_p = .02$	*n.s.* $\eta^2_p = .02$
Moni-toring	$F(1, 80) = 28$ $p < .001$ $\eta^2_p = .26$	*n.s.* $\eta^2_p = .03$	*n.s.* $\eta^2_p = .01$
Mental Arith-metics	$F(1, 79) = 8.78$ $p < .01$ $\eta^2_p = .10$	*n.s.* $\eta^2_p = .02$	*n.s.* $\eta^2_p = .02$

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Table 2. Data is collapsed over the three training groups.
Transfer data on solution time and ERD for each task: Reporting main effects and interactions for an ANOVA with the between-subject factor intelligence-group (lower vs. higher intelligence) and the within-subject factor time (pre- and post-test)

Task	Main effect time	Main effect IQ-group	Interaction time * IQ-group
Solution time			
Task-Switch	$F(1, 80) = 125.66$ $p < .001$ $\eta^2_p = .61$	*n.s.* $\eta^2_p = .01$	*n.s.* $\eta^2_p = .01$
Moni-toring	$F(1, 80) = 28.01$ $p < .001$ $\eta^2_p = .26$	*n.s.* $\eta^2_p = .01$	*n.s.* $\eta^2_p = .01$
Mental Arith-metics	$F(1, 80) = 8.75$ $p < .01$ $\eta^2_p = .1$	*n.s.* $\eta^2_p = .01$	*n.s.* $\eta^2_p = .04$

ERD-total			
Task-Switch	*n.s.* $\eta^2_p = .01$	*n.s.* $\eta^2_p = .01$	*n.s.* $\eta^2_p = .01$
Moni-toring	*n.s.* $\eta^2_p = .01$	*n.s.* $\eta^2_p = .02$	*n.s.* $\eta^2_p = .01$
Mental Arith-metics	*n.s.* $\eta^2_p = .01$	$F(1, 76) = 3.97$ $p < .05$ $\eta^2_p = .05$	*n.s.* $\eta^2_p = .01$

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Table 3. Training results on solution time and ERD for each task: Reporting main effects and interactions for an ANOVA with the between-subject factor intelligence-group (lower vs. higher intelligence) and the within-subject factor time (pre- and post-test)

Task	Main effect time	Main effect IQ-group	Interaction time * IQ-group
Solution time			
1back	$F(1, 23) = 34.38$ $p < .001$ $\eta^2_p = .60$	n.s. $\eta^2_p = .03$	n.s. $\eta^2_p = .01$
1Face	$F(1, 21) = 14.60$ $p < .01$ $\eta^2_p = .41$	n.s. $\eta^2_p = .06$	n.s. $\eta^2_p = .01$
1Letter	$F(1, 23) = 26.65$ $p < .001$ $\eta^2_p = .54$	n.s. $\eta^2_p = .04$	n.s. $\eta^2_p = .01$
3back	$F(1, 23) = 36.81$ $p < .001$ $\eta^2_p = .62$	n.s. $\eta^2_p = .01$	n.s. $\eta^2_p = .01$
4Faces	$F(1, 23) = 52.60$ $p < .001$ $\eta^2_p = .70$	n.s. $\eta^2_p = .11$	n.s. $\eta^2_p = .04$
4Letters	$F(1, 23) = 29.67$ $p < .001$ $\eta^2_p = .56$	n.s. $\eta^2_p = .02$	n.s. $\eta^2_p = .02$
N-back Level			
Dual-N-back	$F(1, 27) = 48.61$ $p < .001$ $\eta^2_p = .64$	n.s. $\eta^2_p = .06$	n.s. $\eta^2_p = .01$
ERD-total			
1back	n.s. $\eta^2_p = .02$	n.s. $\eta^2_p = .05$	n.s. $\eta^2_p = .09$
1Face	$F(1, 25) = 4.80$ $p < .05$ $\eta^2_p = .16$	n.s. $\eta^2_p = .08$	n.s. $\eta^2_p = .03$
1Letter	$F(1, 25) = 4.31$ $p < .05$ $\eta^2_p = .15$ $d = .16$	n.s. $\eta^2_p = .06$	n.s. $\eta^2_p = .01$
3back	n.s. $\eta^2_p = .12$	n.s. $\eta^2_p = .01$	n.s. $\eta^2_p = .02$
4Faces	n.s. $\eta^2_p = .01$	$F(1, 24) = 5.33$ $p < .05$ $\eta^2_p = .18$	n.s. $\eta^2_p = .02$
4Letters	n.s. $\eta^2_p = .01$	n.s. $\eta^2_p = .05$	n.s. $\eta^2_p = .10$
Dual-N-back	n.s. $\eta^2_p = .1$	n.s. $\eta^2_p = .06$	n.s. $\eta^2_p = .01$