NEURAL EFFICIENCY AND MENTAL WORKLOAD: LOCATING THE REDLINE

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ABSTRACT
Mental workload is often measured using multidimensional measures, which aim to identify a 'redline' or region of 'overload' when operator performance is jeopardised by overwhelming levels of cognitive demand. The current paper will address two issues in this field: (1) the role of motivation in mental workload research, particularly with respect to the quantification of workload 'redlines', and (2) the use of composite measures to describe the interaction between performance and neurophysiological activation as an index of neural efficiency. Two studies are summarised where participants experienced various levels of working memory load, from easy to impossible levels of task demand. The first manipulated extrinsic motivation (financial reward) alongside working memory load and measured theta power at frontal-medial location. The second study assessed brain activation with respect to neurovascular activation (via fNIRS) in response to working memory load. Data are provided to demonstrate the sensitivity and potential benefit of neural efficiency as a neuroergonomic index of mental workload.

1. INTRODUCTION

Mental workload has been widely used in human factors research since the publication of two key collections (Hancock & Meshkati, 1988; Moray, 1979), see (Young, Brookhuis, Wickens, & Hancock, 2015) for historical perspective. The measurement of mental workload is particularly important for the assessment of safety-critical performance where high cognitive demand can lead directly to errors and accidents. Therefore, research into mental workload tends to focus on a state of overload where selective attention is disrupted (Lavie, 1995) and performance quality declines (De Waard, 1996). The point where workload becomes overload has been conceptualised as a 'redline' of workload (Wickens & Tsang, 2014), which delineates between: (1) good performance where the operator has sufficient capacity to meet task demands, and (2) declining performance when the cognitive requirements of the task exceed the information processing capacity of the operator - see Fig. 2 in Young, Brookhuis et al (2015) for an illustration. The accurate measurement of the workload redline across multiple operational contexts remains a major challenge for human factors research.

The concept of overload was derived from the Yerkes-Dodson law (Teigen, 1994) and resource-based models of workload and attention (Kahneman, 1973; Navon & Gopher, 1979; Wickens, 1991). This perspective is based upon an assumption that humans have finite limits on information processing capacity (e.g. number of sensory inputs/motor outputs, complexity of inputs/outputs, time available), which can be overwhelmed by task demands. Others have conceptualised overload within an adaptive framework (Hancock & Warm, 1989), highlighting the contribution of strategies and volitional self-regulation to the interaction between operator and task demands. The framework developed by Hockey (Hockey, 1997) took this approach to a logical conclusion by including the possibility that an overloaded operator could effectively withdraw from task demands by reducing performance quality as a strategy to both conserve mental effort and reduce task-related stress.

Motivational intensity theory was originally developed to describe those factors that mediate the interaction between task demand and effort investment (Brehm & Self, 1989; Wright, 1996). This theory is particularly relevant for those self-regulatory concepts of mental overload described in the last paragraph. According to Brehm's original theory, there is a distinction between the level of effort invested in response to demand (motivational intensity) and the maximum effort the individual is willing to invest in order to satisfy a goal associated with successful performance (success importance) (Wright, 2008). Therefore, effort is invested in a proportionate fashion in response to increased task demand until a point is reached where (a) the likelihood of successful performance is assessed to be low, or (b) the consequences of success are perceived to be unimportant or inconsequential with respect to other task-related goals (e.g. to earn money, to develop mastery), at which point effort is withdrawn from the task; see (Richter, Gendolla, & Wright, 2016) for recent review. It is important for measures of mental workload to capture the dynamic relationship between effort investment and demand/performance encapsulated by motivational intensity theory. By representing interaction between user skill and task demand as an adaptive act of self-regulation, we can: (1) identify redlines that are predictive of performance breakdown, and (2) distinguish between varieties of mental overload with respect to effort investment or conservation (Hockey, 1997). It is also necessary to develop composite measures of mental workload that reconcile different dimensions of workload assessment in order to predict performance breakdown, particularly in the context of safety-critical behaviour.

2. NEURAL EFFICIENCY

A number of early neuroimaging studies (R. J. Haier et al., 1988; Parks et al., 1989) studied the relationship between IQ and neurophysiological activation. Their findings demonstrated that participants with higher IQ exhibited lower levels of cerebral metabolism when performing cognitive tasks; in other words, higher IQ individuals performed with greater neural efficiency compared to those with lower IQ scores. This neural efficiency hypothesis has been refined over the subsequent years to reveal a number of significant caveats on this original research (A. C. Neubauer & Fink, 2009). For example, neural efficiency (with respect to a differentiation between higher and lower IQ individuals) was only observed when task difficulty fell in the moderate to high range of cognitive demand (see Fig. 2 in Neubauer & Fink, 2009); hence a cognitive task must stimulate a minimum level of challenge/complexity before we can observe the phenomenon of neural efficiency. On a related note, it was argued that moderate-to-high levels of difficulty allowed participants to develop and utilise efficient cognitive strategies that exhibit neural efficiency as a consequence of skill acquisition (Doppelmayr et al., 2005). With respect to the latter, Haier and colleagues (R.J. Haier et al., 1992) provided participants with 4-8 hours of practice on a computer game; they noted a neural efficiency effect that was associated with both performance improvement (i.e. practice led to improved performance and reduced metabolic activity) and intelligence (i.e. the effects of practice were more pronounced for individuals with higher IQ). A later study (Aljoscha C. Neubauer, Grabner, Freudenthaler, Beckmann, & Guthke, 2004) reported that the phenomenon of neural efficiency was localised to individuals with higher IQ, in other words, the propensity to develop neural efficiency depended on the capacity to learn, which in turn, was related to individual variation with respect to intelligence. As a further caveat, the effects of learning on neural efficiency (i.e. reduced neurophysiological activation with practice) may be specific to only cognitive tasks and not extend to sensory or motor tasks (Kelly & Garavan, 2005). The 2004 study by Neubauer and colleagues also noted that neurophysiological evidence for neural efficiency was localised to the frontal cortex. This effect has been replicated with respect to reduced frontal activation with increased task automaticity (Ramsey, Jansma, Jager, Van Raalten, & Kahn, 2004) and a recent study on decisional conflict using neurovascular (fNIRS) markers of activity in the inferior frontal gyrus (Di Domenico, Rodrigo, Ayaz, Fournier, & Ruocco, 2015).

The neural efficiency hypothesis represents an interaction between neurophysiological activation and task demand/performance effectiveness; this combination of neuroscience and behavioural data captures a basic tenet of neuroergonomics (Parasuraman, 2003) and can be used as the basis for a brain-based index of mental workload wherein measures of performance are combined with neurophysiological activity. Two studies of neural efficiency will be presented in the subsequent section, the first describes an EEG-based study on working memory load in combination with a financial incentive, the second details a fNIRS-based investigation using an identical task manipulation.

3. STUDY ONE

18 participants (9 male) took part in the experiment. Effort was elicited with a continuous matching verbal working memory task known as the n-back task, this particular version was based on the one described by (Gevins et al., 1998). This task required participants to indicate if the currently presented stimulus matched an earlier stimulus presentation. Stimuli were single capital letters drawn at random from the following group of 12: B,F,G,H,K,M,P,R,S,T,X and Z. Participants were required to indicate whether the letter matched the previous one (1-back: easy), or the letter that had appeared four letters earlier (4-back: hard), or the letter that had appear seven letters earlier (7-back: impossible). This task was performed in two short blocks of 100sec for each of the three working memory conditions. Responses were given with a keyboard press of 1 for match and 2 for non-match, using the right index and middle fingers. EEG was recorded from 64 Ag-AgCl pin-type active electrodes mounted in a BioSemi stretch-lycra head cap. Electrodes were positioned using the 10–20 system. For the purpose of the current chapter, we will focus on activity in the theta frequency band (4–7 Hz) obtained from the fronto-central site (Fz). Performance from participants was scored with respect to the percentage of correct responses during the 1-back, 4-back and 7-back tasks. The total power in µV2 was obtained for theta frequency band (4–7 Hz) using Fast Fourier Transform - see (Fairclough & Ewing) for full details of analysis. Both performance and neurophysiological activation in the form of theta power have been plotted in a two-dimensional space in Figure 1 for all three levels of working memory demand.

As expected, neural efficiency is highest during the easy, 1-back version of the n-back; note how highly accurate performance coincides with low levels of neurophysiological activation. The cognitive demand of the task increases significantly as participants transition from the 1-back task where a single letter must be retained and updated in working memory to the demanding 4-back, which requires memorisation and continuous updating of a four-letter sequence. As anticipated, performance accuracy falls from 94% to 76% and this deterioration is accompanied by a significant increase of theta power in the fronto-central region. This transition represents a decline of neural efficiency (i.e. higher neurophysiological activation is required to sustain a lower level of performance) and this pattern is indicative of participants at the limits of their capacity to engage with the cognitive challenge of the task. The 7-back version of the n-back was designed to represent an 'impossible' level of working memory demand. The transition from 4-back to 7-back task (Figure 1) provides an illustration of participants passing from a state of high mental workload to overload, which is characterised by both falling performance and reduced neurophysiological activation. This pattern is indicative of participants who are no longer engaged with the cognitive demand of the task or the pursuit of task-related goals, e.g. mastery, skill acquisition.

The data from study one demonstrate how a composite measure of neural efficiency, representing an interaction between performance/demand and neurophysiological activation, allows us to both visualise the trajectory from low workload to overload and differentiate a number of stages along this continuum . Two distinct phases of neural efficiency can be observed in Figure 1: (1) an inverse correlation as neurophysiological activation increased and performance effectiveness declined as the participants reached the limits of their capacity to perform prior to the 4-back task, and (2) a coupling between falling levels of neurophysiological activation and performance quality when the participants were overloaded.

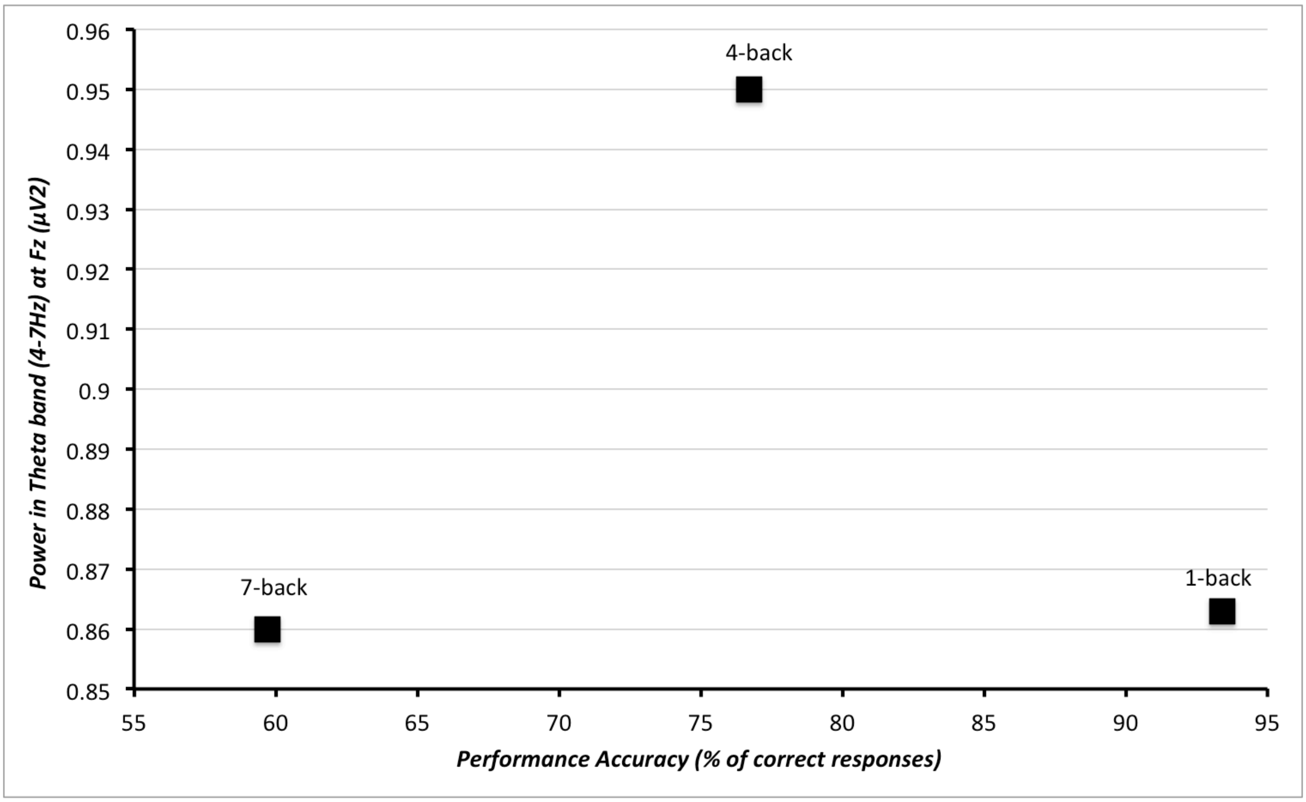

Figure 1. Performance accuracy and power in fronto-central theta during all three levels of working memory demand (1-back, 4-back, 7-back), N=18.

4. STUDY TWO

This experiment (unpublished at the time of writing) utilised a mixed-design wherein working memory load served as a within-participants manipulation. Four versions of the n-back working memory task were used, these were: 0-back (very easy) 1-back (easy), 3-back (hard but success possible), 5-back (very hard and success unlikely) and a 7-back (impossible). 30 people took part in the experiment and they were recruited from the University population of undergraduates and postgraduate students. The mean age of the participants was 26.9 yrs and the sample included an equal number of males and females. A verbal version of the n-back will be used to create all five conditions. During this task, participants are exposed to a sequential presentation of single capital letters, e.g. B, F, R, T, that appear at a rate of approx. 1 item every 1.5sec. The participant must respond to each letter with one of two possible responses, either the letter is the same as the previous letter (a 'match') or the letter is different (a 'non-match'). Participants are required to perform this task continuously for a period of approximately 2 minutes.

A fNIR Imager1000 and COBI data collection suit (Biopac System Inc) was used for data collection. The 16 channel probe is placed on the forehead aligned to Fp1 and Fp2 of the international 10-20 system, and rotated so that Fpz corresponded to the midpoint of the probe. Areas underlying the 16 voxels are right and left superior and inferior frontal gyrii (BA10 and BA46). The current analysis will focus on the right-lateral area of the PFC that was approximates the right side of BA46. The fNIRS device captures relative changes in oxygenated (Hb0) and deoxygenated haemoglobin (Hbb), it is assumed that neuronal activation is represented by a process of neurovascular coupling where increased levels of Hb0 are accompanied by decreased Hbb, see (Scholkmann et al., 2014) for review and further explanation. For the purpose of the current analysis, we shall focus on decreased Hbb as a marker of neurophysiological activation.

The relationship between neurophysiological activation and task performance across all five levels of working memory load is illustrated in Figure 2. The 0-back condition serves as a control for the motor demands of the task because participants were required to simply press a button when a letter appeared on the screen, hence performance is close to perfect and neurophysiological activation is low. When workload increases from the 0-back to the 1-back task, neurophysiological activation increases sharply but performance remains at a stable and high level. The transition from 1-back to 3-back represents a more substantial increase of task demand. As shown in Figure 2, neurophysiological activation increases slightly but there is a conspicuous decline in performance quality. As workload passes from the realm of challenging demand (3-back) to the rigours of the 5-back where demand is very high with low likelihood of success, the continued degradation of performance is now accompanied by a fall of neurophysiological activation. Unsurprisingly, this trend is accelerated for the impossible 7-back condition as neurophysiological activation falls to a similar level as was observed for the 0-back. With respect to identifying regions of mental workload, there are two significant transitions in Figure 2: (1) reduced performance and increased neurophysiological activation from 1-back to 3-back that indicates engagement despite declining performance, and (2) reduced performance in combination with diminished neurophysiological activation from 3-back to the 5-back, which is representative of a redline.

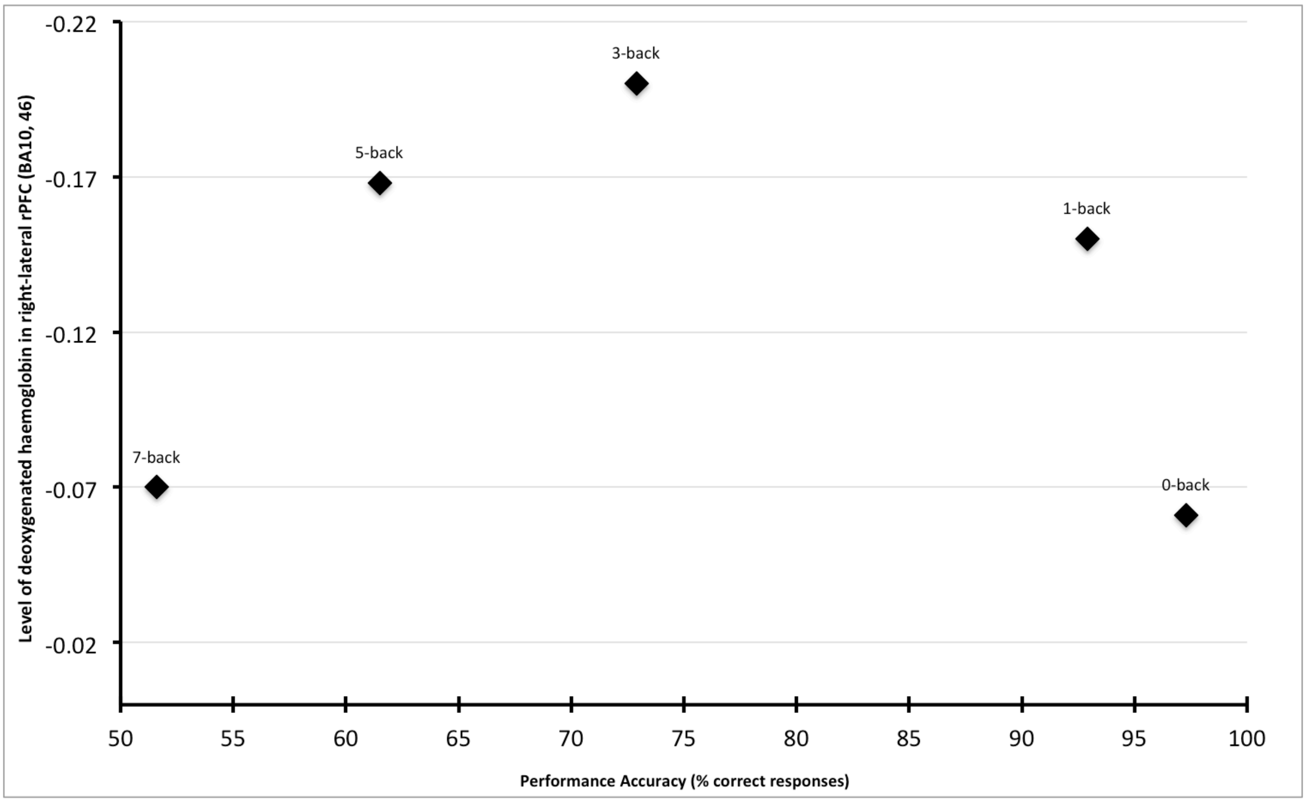

Figure 2. Performance accuracy and level of deoxygenated haemoglobin in right-lateral area of the rostral prefrontal cortex during all five levels of working memory demand (N=30). Note: decreased levels of deoxygenated haemoglobin are associated with neurophysiological activation.

5. SUMMARY

A combination of measures derived from behaviour and neuroscience can be used to delineate regions of mental workload, from low demand to overload. These regions are defined by the dynamic relationship between two workload measures, captured here as an index of neural efficiency. By definition, low mental workload is an efficient combination of good performance and low neurophysiological activation. Overload is also characterised by low neurophysiological activation but in combination with poor performance. It is the identification of critical transitions between these two extremes that represents the value of the current approach. These transitions are defined by the direction of change observed simultaneously in measures of performance and neurophysiological activation. When neurophysiological activity increases or remains stable in the face of declining performance, we can infer that: (1) the individual remains engaged with task goals and believes successful performance to be a possibility, and (2) the individual is challenged by the demands of the task. Within this scheme, the workload redline is defined by a triad of: high task demands, falling performance quality and reduced neurophysiological activation.

REFERENCES

Brehm, J. W., & Self, E. A. (1989). The intensity of motivation. *Annual Review of Psychology, 40*, 109-131.

De Waard, D. (1996). *The Measurement of Driver Mental Workload.* Rijksuniversiteit Groningen, Groningen, The Netherlands.

Di Domenico, S. I., Rodrigo, A. H., Ayaz, H., Fournier, M. A., & Ruocco, A. C. (2015). Decision-making conflict and the neural efficiency hypothesis of intelligence: a functional near-infrared spectroscopy investigation. *NeuroImage, 109*, 307-317. doi:10.1016/j.neuroimage.2015.01.039

Doppelmayr, M., Klimesch, W., Sauseng, P., Hodlmoser, K., Stadler, W., & Hanslmayr, S. (2005). Intelligence related differences in EEG-bandpower. *Neuroscience Letters, 381*, 309-313.

Fairclough, S. H., & Ewing, K. The effect of task demand and incentive on neurophysiological and cardiovascular markers of effort. *International Journal of Psychophysiology*. doi:http://doi.org/10.1016/j.ijpsycho.2017.01.007

Gevins, A., Smith, M. E., Leong, H., McEvoy, L., Whitfield, S., Du, R., & Rush, G. (1998). Monitoring working memory load during computer-based tasks with EEG pattern recognition models. *Human Factors, 40*(1), 79-91.

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

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

Hancock, P. A., & Meshkati, N. (1988). *Human Mental Workload*. Amsterdam: North-Holland.

Hancock, P. A., & Warm, J. S. (1989). A dynamic model of stress and sustained attention. *Human Factors, 31*(5), 519-537.

Hockey, G. R. J. (1997). Compensatory control in the regulation of human performance under stress and high workload: a cognitive-energetical framework. *Biological Psychology, 45*, 73-93.

Kahneman, D. (1973). *Attention and Effort*. Englewood Cliffs N. J.: Prentice-Hall.

Kelly, A. M. C., & Garavan, H. (2005). Human Functional Neuroimaging of Brain Changes Associated with Practice. *Cerebral Cortex, 15*(8), 1089-1102. doi:10.1093/cercor/bhi005

Lavie, N. (1995). Perceptual load as a necessary condition for selective attention. *Journal of Experimental Psychology: Human Perception and Performance, 21*(3), 451-468.

Moray, N. (1979). Mental Workload: Its Theory and Measurement. New York: Plenum.

Navon, D., & Gopher, D. (1979). On the economy of the human-processing system. *Psychological Review, 86*(3), 214-225.

Neubauer, A. C., & Fink, A. (2009). Intelligence and neural efficiency. *Neurosci Biobehav Rev, 33*(7), 1004-1023. doi:10.1016/j.neubiorev.2009.04.001

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. doi:http://dx.doi.org/10.1016/j.actpsy.2003.11.005

Parasuraman, R. (2003). Neuroergonomics: research and practice. *Theoretical Issues in Ergonomic Science, 4*(1-2), 5-20.

Parks, R. W., Crockett, D. J., Tuokko, H., Beattie, B. L., Ashford, J. W., Coburn, K. L., . . . McGeer, E. G. (1989). Neuropsychological 'system efficiency' and positron emission topography. *Journal of Neuropsychiatry, 1*, 269-282.

Ramsey, N. F., Jansma, J. M., Jager, G., Van Raalten, T., & Kahn, R. S. (2004). Neurophysiological factors in human information processing capacity. *Brain, 127*(3), 517-525. doi:10.1093/brain/awh060

Richter, M., Gendolla, G. H. E., & Wright, R. A. (2016). Three Decades of Research on Motivational Intensity Theory. *3*, 149-186. doi:10.1016/bs.adms.2016.02.001

Scholkmann, F., Kleiser, S., Metz, A. J., Zimmermann, R., Mata Pavia, J., Wolf, U., & Wolf, M. (2014). A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. *NeuroImage, 85 Pt 1*, 6-27. doi:10.1016/j.neuroimage. 2013.05.004

Teigen, K. H. (1994). Yerkes-Dodson: A law for all seasons. *Theory and Psychology, 4*(4), 525-547.

Wickens, C. D. (1991). Processing resources and attention. In D. L. Damos (Ed.), *Multiple-Task Performance* (pp. 3-34). London: Taylor and Francis.

Wickens, C. D., & Tsang, P. (2014). Workload. In F. Durso (Ed.), *Handbook of Human-Systems Integration*. Washington DC: APA.

Wright, R. A. (1996). Brehm's theory of motivation as a model of effort and cardiovascular response. In P. M. Gollwitzer & A. Bargh (Eds.), *The Psychology of Action: Linking Cognition and Motivation to Behaviour* (pp. 424-453). New York: Guilford Press.

Wright, R. A. (2008). Refining the prediction of effort: Brehm's distinction between potential motivation and motivation intensity. *Social and Personality Psychology Compass, 2*(2), 682-701.

Young, M. S., Brookhuis, K. A., Wickens, C. D., & Hancock, P. A. (2015). State of science: mental workload in ergonomics. *Ergonomics, 58*(1), 1-17.