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Editorial

If you are reading this Editorial, it is likely because you are contemplating diving into the set of articles that comprise this *Neuropsychologia Special Issue*. The decision-making that is part and parcel of such contemplation may involve the trade-off between the benefits of reading a set of articles that are likely of high intrinsic interest and motivational value to you, relative to the expenditure of cognitive effort that it will take to read, process, and fully synthesize them. However, these types of contemplations also seem to beg a number of fundamental questions: Why does it feel so effortful to think long and hard? Even when it is deemed to be valuable, why are we often so stingy about our cognitive effort, sometimes even avoiding it altogether? And more to the point, what are the associated behavioral phenomena, computational mechanisms, and neurobiological processes that accompany decision-making and engagement in cognitive effort?

These questions are not only fascinating, but also increasingly relevant, as modern life places ever-greater demands on cognitive control for attention, planning, reasoning, and decision-making. Moreover, these demands are brought into sharp relief when considering the challenges faced by those with schizophrenia, ADHD, depression, Parkinson's disease, and other disorders that all clearly seem to impact cognitive motivation. Consequently, there has been a resurgence of interest and research attention given towards advancing our scientific understanding of the nature of cognitive effort.

1. A Brief History of Cognitive Effort

As a psychological construct, cognitive effort has received continuing interest for decades. One of the earliest influential treatments came from Kahneman's landmark monograph *Attention and Effort* (Kahneman, 1973), which sparked an enduring program of research on measuring mental effort via psychophysiological indices, such as pupil dilation and cardiovascular reactivity, e.g. (Brehm and Self, 1989; Wright, 1996). Likewise, there has been a continuing focus on the intuitive notion that mental effort requires metabolic or energetic resources, e.g. (G. Hockey and Robert, 2011; Robert and Hockey, 1997). This perspective culminated in the highly influential 'ego depletion' hypothesis (Baumeister et al., 1998), which spawned a prolific line of research. These investigations were aimed at testing the specific prediction that sustained cognitive demands reduce performance in subsequent tasks, and that reduced performance reflected resource depletion by sustained demands (Gailliot and Baumeister, 2007). Subsequent research, however, has fostered skepticism regarding putative depletion effects, as chronicled in meta-analyses and reports of failures to replicate (Carter et al., 2015; Hagger et al., 2010). Indeed, a number of follow-up studies have suggested that depletion effects may simply reflect experimenter demand characteristics and context framing rather than resource depletion (Job et al., 2013). While the ego-depletion

literature highlights the role of volitional engagement in task performance, inconsistent results indicate that better operational definitions and experimental paradigms are needed. It is here that neuroscience-based approaches have offered increased experimental traction and promoted renewed excitement about the potential for progress.

A key problem from the outset has been the challenge of defining 'cognitive effort' in an operationally useful and non-circular manner. In recent years, cognitive effort has referred alternately to the volitional, regulatory aspects of task engagement mediating performance under cognitive control demands (Shenhav et al., 2017), or as the subjective, affective consequences of responding to those demands (Botvinick, 2007). These definitions have led to a shift in methodological focus towards approaches that lend themselves to more precise quantification of effort in terms of behavioral patterns including demand avoidance (Kool et al., 2010) and effort discounting (Libedinsky et al., 2013; Westbrook et al., 2013), which have been explored in decision-making paradigms.

The complementary utilization of decision-making and regulatory performance paradigms has proven to be a critical advance. Were cognitive effort defined with respect to performance only, for example, it would be unclear whether increased performance indicates increased exertion at higher subjective costs, or decreased subjective costliness, increasing a participants' willingness to engage. In other words, the primary experimental tactic has been to design paradigms in which participants could explicitly engage with or avoid demands, thus simultaneously demonstrating that engagement is volitional, and quantifying the subjective costliness of engagement. This basic approach has been instrumental in a rapidly expanding "next generation" of cognitive effort studies defining the boundaries between "hard" capacity limits, and "soft" motivational and volitional factors. Moreover, it has informed theoretical development into fundamental questions about the nature and implications of cognitive effort. This theoretical development has been strongly influenced by reinforcement learning and neuroeconomics literatures (Botvinick and Braver, 2015; Shenhav et al., 2013) as well as computational approaches that invoke concepts such as meta-learning and meta-control (Boureau et al., 2015; Musslick et al., 2015). Likewise, these theoretical and experimental approaches provide a natural leverage point for cognitive neuroscience studies. In particular, they provide more sensitive metrics with which to isolate the neural systems that not only support performance during effortful tasks, but also those which enable decision-making about such tasks, and are engaged by motivational factors that can be monitored or manipulated.

The intent of this *Neuropsychologia* Special Issue is to shine a spotlight on this newly burgeoning research addressing cognitive effort from a neuroscientific perspective, and moreover, to highlight key outstanding questions for future research. Indeed, we were gratified that the articles submitted in response to our call for manuscripts

illustrate nicely the depth and breadth of this growing field. Several core themes emerged including: 1) the nature of cognitive effort costs, 2) the mechanisms of cost monitoring and decision-making, 3) physiological signatures of cognitive effort expenditure, 4) implications for effort and reward processing in health and disease. We next provide an overview to these themes, along with pointers to the relevant *Special Issue* contributions.

2. The Cost of Cognitive Effort

One fundamental outstanding question regarding the nature of cognitive effort costs is: why is cognitive control effortful at all? Especially if, as highlighted in submissions by *Zénon et al.* and *Manohar et al.*, cognitive control does not increase global brain metabolism in the same way that the metabolic costs of lifting a weight might justify the subjective costliness of physical exertion. One idea, investigated by *Otto and Daw*, is that cognitive control is costly because it requires precious resources which may be useful for pursuing alternative opportunities. As such, cognitive control necessarily incurs opportunity costs, cf. (Boureau et al., 2015; Kurzban et al., 2013), and should be treated as costly when average reward rates are high. Opportunity cost hypotheses dovetail nicely with another recent proposal that the subjective costliness of cognitive control serves the purpose of moderating a stability-flexibility tradeoff. Namely, subjective costs bias against deep, stable engagement in a single task so that neural states implementing control processes can be flexibly reconfigured for alternative opportunities (Musslick et al., 2018). Another idea from *Zénon et al.* builds on information theoretic models of cognitive control (Koechlin and Summerfield, 2007) to argue that cognitive control demands, whether stemming from novelty, task switching, or the need to overcome prepotent responses, require relatively large information gain. This information gain corresponds with high representational complexity, which is treated as costly in brain systems biasing efficient coding. Thus our brain is biased against control itself, perhaps for reasons of metabolic costliness (increased complexity increases demand for metabolic inputs locally, thus reducing supply in other regions), opportunity costliness (complexity reduces bandwidth for other representations), or other to-be-articulated mechanisms biasing coding efficiency.

3. Effort Monitoring

If we treat control as costly, we must have the capacity to track effort costs. But what kinds of information would we track? On a cognitive level, one proposal is that subjective effort tracks demands for cognitive control. According to an influential account (Botvinick, 2007), the anterior cingulate cortex (ACC) monitors for response conflict and, when it is detected, the ACC both recruits cognitive control to resolve the conflict and also triggers an aversive learning signal to bias avoidance of contexts giving rise to conflict in the first place. Consequences of this learning signal would be subjective costliness and demand aversion. The potential upside of avoidance, however, is that we allocate more of our time to pursuits that are associated with more certain reward and higher expected value. One compelling theory is that the ACC may regulate cognitive control not just reflexively when conflict is detected, but according to the expected value of control, taking into account both potential reward benefits and effort costs (Shenhav et al., 2013). Another proposal, complementing the hypothesis that we track conflict to maximize expected reward, is that we might also track errors for the same purpose. *Benoit et al.* provide new evidence that participants increasingly avoid demands as their performance falls. Their results support the hypothesis that we monitor performance to strategically avoid high demands and falling short in the future when negative outcomes accumulate. Interestingly, whether we are consciously aware of differences in demand may also influence the subjective costliness of a task. *Dunn et al.,* provide evidence that cues

promoting explicit awareness of differences in task demands also promote demand avoidance. This result is useful, in part, because it helps resolve an open question about cognitive effort and schizophrenia. Namely, recent literature has shown conflicting evidence that patients with schizophrenia find cognitive demands more costly (Culbreth et al., 2016), and yet avoid cognitive demands less than healthy controls (J. M. Gold et al., 2014). One possible resolution of these seemingly discrepant results is that schizophrenia patients may not avoid control in some tasks because they lack conscious awareness of subtle differences in demands. Future work is needed to understand why individuals with schizophrenia might be relatively unable to track cognitive demands and, more broadly, what kinds of information might engender subjective effort and demand avoidance in healthy and disordered populations.

4. The Neurobiology of Cognitive Effort

Another fundamental question relates to how cognitive effort is registered at the neural level. As noted, one hypothesis is that when the ACC detects response conflict, it transmits an aversive learning signal which might effect effort cost learning via phasic dopamine dips (Botvinick, 2007; Cavanagh et al., 2014). Supporting this hypothesis, *Albrecht et al.* provide data suggesting that the difference between healthy controls' and schizophrenia patients' ability to track effort demands may stem, in part, from attenuated mid-frontal theta (MFT) signals, originating in the ACC, in schizophrenia. Individuals may track MFT power as an index of subjective effort costs, or rely on accruing reward and punishment statistics encoded in synaptic weights at downstream dopaminergic targets. Relatedly, *Umemoto et al.* also employed EEG to reveal interesting interactions between incentives, control demands, and MFT power on task performance over many trials. Their findings suggest that MFT power might be an indicator of increasing control intensity, or increasing fatigue. While the specific assignation remains unresolved, these reports strongly motivate MFT power as a candidate index of cognitive demands and effort cost learning, across motivational states. They also, in conjunction with other work on dopamine and effort, suggest that downstream dopamine targets like the striatum may cache effort costs for effort-based decision-making across task contexts (Froböse and Cools, 2018; Westbrook and Braver, 2016). This conclusion aligns well with a cross-sectional, developmental study by *Niebaum et al.* implicating the prefrontal cortex and its connectivity to the striatum as being critical to demand awareness and avoidance. Specifically, they show that while cognitive demand avoidance was present in adult and 11-12 year olds, it was absent in 6-7 year olds. They interpret their result, in light of other recent developmental studies, as indicating that immature prefrontal-striatal connectivity in 6-7 year olds explains their inability to bias behavior away from cognitive effort. Collectively, these studies highlight an emerging set of hypotheses about what neural dynamics signal effort, where such experiences of effort are cached, and how they are retrieved during effort-based decision-making.

Several submissions focused on the physiological signatures that accompany effort exertion. This theme has both practical significance (if one wanted to probe the brain to measure exertion, what should they measure?), and theoretical implications (if the brain were monitoring exertion, what would it monitor?). One possibility is neurotransmitter release. As highlighted by *Müller and Apps*, for example, acetylcholine or norepinephrine might be critical for supporting sustained attention, particularly under fatigue when attention is likely to lapse. *Manohar et al.* also implicate neurotransmitter function by highlighting that effort might be closely related to neuronal gain adjustments to drive negative feedback required to maintain control states. Specifically, they adapt optimal motor control models to incentivized saccade data to argue that behavioral control is instantiated by stable neural activity patterns (e.g. rule representations), and that persistent negative feedback is needed to maintain stability. Although their modeling does not

address which neural systems implement negative feedback, their results support the hypothesis that feedback gain is a central result of motivated control. Thus, taken together with evidence that that neuronal gain may be regulated, in part, by catecholamine function (Aston-Jones and Cohen, 2005; Cools and D'Esposito, 2011), neurotransmitter function becomes a strong candidate channel of cognitive effort exertion.

While tracking neurotransmitter release itself is difficult in humans, a number of studies in this Issue have examined pupil dilation – thought to index both catecholamine and ACC function (Aston-Jones and Cohen, 2005; Joshi et al., 2016; Nieuwenhuis et al., 2005) – in response to incentives and cognitive demands. *Kostandyan et al.*, for example, show that pupil dilation patterns track both sustained incentive context and trial-by-trial incentive cues, suggesting that pupil dilation offers fine-grained information about incentive motivation. Relatedly, *Massar et al.* find systematic pupil dilation patterns that predict performance as a function of sleep deprivation, control demands, and incentives. Interestingly, in addition to replicating a prior result that sleep deprivation increases subjective effort costs, the researchers also demonstrated that pupil dilation tracks performance as a function of its value. This finding is consistent with the hypothesis that control is not a reflexive response to demands, but rather is regulated based on both the costs and benefits of control allocation.

Brain imaging studies are playing a central role in elucidating the neural systems underlying effort exertion. A primary hypothesis – stemming from the observation that cognitive control is treated as costly, is that increasing activity in frontoparietal control networks (FPN) constitutes exertion of cognitive effort. In support of this prediction, *Vassena et al.* have used fNIRS to show that anticipation of cognitive demands was associated with increased activity in the dorsolateral prefrontal cortex, and moreover, that the degree of activity increase predicted task performance and liking. These findings support the hypothesis that the engagement of preparatory control processes is determined by the expected value of control. *Sayali and Badre* pursued a related question, using fMRI to investigate the degree to which large-scale brain networks track subjective effort expenditure, and predict demand avoidance. After selecting participants with reliable demand avoidance, they utilized principal components analysis to identify brain networks that exhibited a high degree of internal coherence in their response to increasing cognitive demands. The key finding was that FPN showed a parametric increase, while the default mode network (DMN) parametrically decreased with cognitive demands; however, only DMN suppression predicted the degree of demand avoidance. Thus, paradoxically, it may be that DMN suppression is the best neural index of subjective effort. Perhaps, task-negative DMN suppression could be a more reliable index of effort exertion because it encodes a single, undifferentiated channel of engagement in contrast with varying degrees of activation across multiple task-positive networks.

5. Reward Benefits and Effort Costs in Health and Disease

The implications of cognitive effort, including effort discounting and demand avoidance are widespread, with implications for both healthy and diseased populations. In addition to implications for schizophrenia addressed by *Albrecht et al.*, there is reason to think exaggerated effort costs or deficient effort expenditure may account for cognitive deficits in disorders ranging from ADHD to Parkinson's disease to depression. For example, as described by *Müller and Apps*, subjective effort costs may be exaggerated as a result of clinical fatigue, as observed in stroke patients, or following problem inflammation which has elsewhere been shown to impact effort sensitivity in humans (Draper et al., 2017). Beyond effort costs, cognitive effort may also impact how we process rewards themselves. *Milyavskaya et al.* for example, describe EEG results highlighting how the experience of rewards may differ based on whether these were received in relationship to the expenditure of cognitive effort, or instead when sustaining attention

throughout a boring task. Finally, *Sullivan-Toole et al.* point out that there are interesting interactions to explore in the domain of social reward processing, since effort may impact the receipt of rewards differentially depending on whether we work to win rewards for ourselves, or on behalf of others. Moreover, they raise numerous questions for future research in disorders that have a clear social component (e.g., autism, psychopathy, social anxiety disorder), since effort and reward sensitivity may influence willingness to expend cognitive effort on others' behalf, empathize with others' mental states, and account for others' cognitive effort costs. Finally, the implications of these cognitive effort investigations extend widely beyond the clinic as well, given that cognitive effort impacts everything from student performance in academic settings to careers involving sustained attention, reasoning, planning, and decision-making.

As demonstrated by our brief summary of this *Special Issue*, research on cognitive effort is rapidly diversifying, addressing an ever-growing array of questions with broad implications for normal and disordered functioning. We hope that the *Special Issue* will stimulate future research endeavors and help to coordinate new investigations that bridge theoretical perspectives, methodologies, and cut across health and disease, in addressing core, outstanding questions about cognitive effort.

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