

**Your Attention Please: Neural Networks, Individual Differences, and  
Clinical Implications of Attentional Control in the Human Brain**

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## Abstract

Our brain's ability to direct our attention requires paradoxical processing. We must be able to focus and maintain our attention without allowing external stimuli to lure us off task. Yet, we must also be able to shift our attention flexibly to switch tasks in response to relevant cues. Unitary accounts of attention maintain that these abilities rely on similar or identical neurocognitive mechanisms, while fractionated models propose that these are dissociable processes. Here, we investigated the relationship between sustained attention and task switching both behaviourally and at the level of the brain. We conducted a confirmatory factor analysis of participants' performance on several cognitive switching and sustained attention tasks and found that the observed pattern of performance is consistent with two separate but related factors. We then extended these findings using neuroimaging methods. A multivariate, data-driven analysis of brain activity revealed that sustained attention and task switching are also associated with distinct patterns of activation across the brain. Behavioural performance on each type of task correlated with activity in non-overlapping frontoparietal areas. As participants' reaction time increased over time on a task of sustained attention, they recruited a set of right-lateralized regions associated with stimuli-related processing. Concurrently, when participants showed greater differences in reaction time between switch trials and repeat trials, they recruited areas associated with enhanced goal-directed processing in both hemispheres. Our results provide compelling evidence for the dissociation of sustained attention and task switching, both in terms of behavioural performance and patterns of brain activity. We review these findings in the context of existing models of attention and discuss possible clinical implications.

## **Dedication**

To my mom,  
who pushed me to climb the highest mountain peak.

To my dad,  
who always made me believe I could do it.

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**Your Attention Please: Neural Networks, Individual Differences, and  
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Attention is the lens through which we see the world. Our attention is directed and divided, sustained over time, and shifted. The underlying mechanisms of attentional control have been the subject of decades of speculation, careful investigation, and theorizing. While our understanding of individual aspects of attention has become increasingly established, the nuances of the interplay between them remain an open question. Many competing accounts of the executive control of attention exist, which make various predictions about the relationship between different types of attentional processes (e.g., Corbetta & Shulman, 2002; Mesulam, 1981; Norman & Shallice, 1986; Posner & Petersen, 1990). It is possible that different processes are entirely independent, closely related, or even at odds in terms of underlying neural mechanisms.

For instance, the dynamic between sustaining and shifting attention has yet to be established. The ability to successfully maintain focus over time seems intrinsically at odds with the ability to rapidly and flexibly shift focus, yet unitary models of attention would predict that the same executive system mediates both these processes (e.g., Duncan et al., 2000; Niendam et al., 2012; Stuss et al., 1995). Vigilance and shifting are two critical aspects of the top-down control of attention. Nonetheless, sustained attention is absent from most models of executive functioning, and task switching is rarely discussed in existing models of attention. They are two complementary aspects of cognition that have been separated by largely isolated bodies of literature. The current work attempts to bridge this gap by investigating the nature of the relationship between the sustaining attention on a task and switching.

Understanding the dynamic between these two processes is a particularly timely question, given the dramatic increase in the use of digital technologies which constantly pull and divide our attention. The rise of the rapid and continuous redirection of attention between tasks and devices has presented new challenges for our attentional systems. Anecdotal evidence in the popular media would have us believe that this increased familiarity with task-shifting comes at the expense of our ability to sustain attention (e.g., McSpadden, 2015; Richtel, 2010). This matter has also become the subject of formal empirical investigation, as the body of evidence on the use of digital technologies continues to grow, particularly in the context of academic success (e.g., Bellur et al., 2015; Sana et al., 2013; Taneja et al., 2015; Wood et al., 2012). This modern problem assumes a dichotomous system where sustaining attention competes against task switching, but this hypothesis has never been directly tested. Alternatively, if both processes rely on a unitary attention system, where a singular mechanism directs the focus of attention, one process should not impede the other.

### **Sustained Attention**

Sustained attention, also known as “vigilance” or “tonic alertness,” is the ability to maintain focus on a simple, monotonous, and lengthy task where the relevant stimuli occur only rarely (Grahn & Manly, 2012; Langner & Eickhoff, 2013; Warm et al., 2008). Sustained attention is not simple “arousal” on the sleep-wake spectrum, but rather the deliberate, goal-directed maintenance of attention of a given task (Oken et al., 2006; Sarter et al., 2001). It also excludes more complex forms of attention, such as selective or divided attention, and executive functions such as inhibition and working memory (Langner & Eickhoff, 2012).

### *Sustained Attention Tasks*

The empirical study of vigilance began during the Second World War, when Norman Mackworth developed the classic Clock Test, designed to simulate the experience of monitoring a radar screen (Mackworth, 1948) and determine why radar operators' ability to detect submarines declined over long shifts (Warm et al., 2008). The original Mackworth Clock Test lasted over two hours. As predicted, participants' ability to detect subtle "double-jumps" on the clock face declined, and reaction time (RT) increased reliably over time.

In 1956, Rosvold and his colleagues developed the continuous performance task (CPT) to investigate attentional capacity in individuals with brain damage (Rosvold et al., 1956). This was the first CPT to use a sequential presentation of letters where participants were told to press a key whenever they saw the letter "X," while inhibiting responses to all other letters (for review see Riccio et al., 2002). A variety of CPTs have proliferated in the literature, lasting from a few minutes to several hours. Tasks include simple continuous stimulus detection (which assesses "intrinsic alertness" using RT), continuous stimulus discrimination (which assesses vigilance decrement using RT and error rate change), and sustained covert counting of target stimuli (which assesses overall sustained attention using accuracy)(Langner & Eickhoff, 2012; Riccio et al., 2002). Of these, continuous stimulus discrimination tasks provide the most data, allowing for the analysis of fluctuations in accuracy and RT over time (Riccio et al., 2002).

CPTs are intrinsically simple tasks. As such, researchers have introduced numerous manipulations of working memory and perceptual demands in an attempt to reduce ceiling effects. Unfortunately, these manipulations also threaten construct validity and process

purity (Ballard, 1996; Parasuraman et al., 1991; Riccio et al., 2002; Robertson et al., 1997; Shalev et al., 2011). These tasks were also susceptible to automatic, pre-attentional processing of target stimuli (Robertson et al., 1997; Shalev et al., 2011). Two tasks that take different approaches to address these shortcomings have emerged as valid alternatives to the classic CPTs and have come to dominate the sustained attention literature.

First, there is the Sustained Attention to Response Test (SART). The SART was developed by Robertson and his colleagues (1997) to study brain injury patients' everyday attention failures. Existing clinical tools required mental calculation and rapid cognitive processing in addition to sustained attention and so were too complex for use in this population (Robertson et al., 1997). To address the possible automation of response, the SART reversed the pattern of response to target stimuli, requiring participants to respond to all stimuli, and withhold their response on target trials.

Second, there is the Conjunctive Continuous Performance Task (CCPT), Designed by Shalev and colleagues (Shalev et al., 2011; Tsal et al., 2005). The CCPT kept the traditional response-to-target design but made the target stimuli a specific conjunction of two attributes (colour and shape, for example). This conjunction of features made any pre-attentive processing of the target stimuli impossible, as the participant is required to bind two elements to identify a potential target (Shalev et al., 2011; Treisman & Gelade, 1980). In requiring a response to a target stimulus, the CCPT also avoids the possible confound of inhibitory control required on target trials – a potential drawback of the SART.

### ***Vigilance Decrement***

The primary measure of sustained attention is “vigilance decrement,” that is the decline in performance, both in error rate and RT, as a function of time-on-task. Vigilance

decrement can appear within the first 5 minutes of a vigil (Ballard, 1996; Warm et al., 2008), though the decline in performance observed in CPTs is not as steep as in the classic sensory-detection vigilance tasks of the past (Ballard, 1996). Ballard (1996) recommended that continuous performance tasks should last at least 10 minutes to observe noticeable decrements in performance. The inclusion criteria for Langner and Eickhoff's 2011 meta-analysis of sustained attention is therefore far from ideal, as they specified a minimum task length of only 10 seconds. It also highlights the difference between recent research on "task set maintenance" (e.g., Donaldson et al., 2001; Dosenbach et al., 2006, 2007) and canonical sustained attention, as tasks in the "set maintenance" literature are all less than two minutes (and more often only approximately 30 seconds.) Paradigms requiring focus on the order of seconds do not present enough of a challenge to attentional systems to stay on task, and so do not elicit vigilance decrement (Ballard, 1996; Grier et al., 2003; Warm et al., 2008).

Participants' performance on sustained attention tasks can be assessed in a variety of ways. Sensitivity to targets overtime may be modeled using Signal Detection Theory (Ballard, 1996; Parasuraman, 1979; Sarter et al., 2001). However, most authors that directly assess vigilance decrement do so by comparing participant's performance across different epochs of the task; Mackworth's original 1949 work did this, as did Shalev et al. in their development of the CCPT (Shalev et al., 2011). However, it is also common to consider only the overall error rate as a simple measure of sustained attention, without examining decrement per se. In fact, the SART does not show reliable time-on-task effects (Robertson et al., 1997; Smilek et al., 2010), and so, only the overall error rate is used as a measure of sustained attention in this task.

There has been some debate over the mechanisms underlying performance decline

in sustained attention tasks (Head & Helton, 2014; Langner & Eickhoff, 2012; Pattyn et al., 2008). “Underload theories” point to mindlessness and boredom, resulting in disengagement from task requirements (Hunter & Eastwood, 2016; Robertson et al., 1997; Pattyn et al., 2008). In line with this theory, cognitively unchallenging tasks produce more significant decrements (Langner & Eickhoff, 2012; Robertson & O’Connell, 2010), as do lower and unpredictable incidence of targets (Parasuraman et al., 1991; Sarter et al., 2001). “Overload theories” invoke a depletion of cognitive resources. In this view, performance decline is due to mental fatigue; the cognitive energy required to maintain focus is depleted over time, making attentional lapses and drifts more common with increasing time-on-task. (Grier et al., 2003; Head & Helton, 2014; Helton & Warm, 2008; Warm et al., 2008; Smit et al., 2004). Factors known to reduce sustained attention performance, such as high event rates, increased demands on working memory, and difficult-to-detect target stimuli corroborate this hypothesis (Ballard, 1996; Sarter et al., 2001). Though a mix of top-down (endogenously-controlled) and bottom-up (stimulus-driven) factors are likely involved in sustaining attention (Langner & Eickhoff, 2012), the majority of the behavioural literature, along with a growing body neuroimaging findings (see below), is more consistent with the “overload theory” of vigilance. These findings demonstrate that sustained attention is similar to executive functions, such as working memory, inhibition, and task shifting, in that it is cognitively effortful, involves controlled processing, and is directed towards an external goal.

### ***Neural Substrates of Sustained Attention***

Many neuroimaging studies have investigated the brain regions associated with performing sustained attention tasks. Positron Emission Tomography (PET) and early

functional Magnetic Resonance Imaging (fMRI) studies of vigilance in the 1990s established the existence of a right-lateralized frontoparietal network underlying sustained attention (e.g., Coull et al., 1996, 1998; Lewin et al., 1996; Pardo et al., 1991; Paus et al., 1997; Sturm et al., 1999). Subsequent fMRI studies have generally replicated these early findings (e.g., Lawrence et al., 2003; O'Connor et al., 2011). Reviews of the literature consolidating evidence from neuroimaging, clinical neuropsychology, and animal models (such as Langner & Eickhoff, 2013 and Sarter et al., 2001), describe the dual nature of sustaining attention. Vigilance integrates both top-down and bottom-up processing and involves both transient and sustained processes. It involves the frontal, parietal, and subcortical regions (namely the thalamus and the basal forebrain) and relies mostly on acetylcholine signaling (Langner & Eickhoff, 2013; Sarter et al., 2001).

Solidifying the link between these regions and behaviour, Lawrence et al. (2003) identified brain areas associated with both good and poor performance during a sustained attention task using exploratory factor analysis. They found that increased Blood-Oxygen-Level-Dependent (BOLD) response in a mostly right-lateralized frontoparietal network, coupled with decreased BOLD response in mainly left-lateralized temporo-limbic areas, correlated with enhanced task performance (better detection of target stimuli). Areas associated with both lower RT and greater accuracy included the bilateral parietal lobes and multiple regions of the prefrontal cortex (PFC), including the bilateral pre-supplementary motor area (pre-SMA) and middle frontal gyri (MFG), the right medial PFC and inferior frontal gyrus (IFG). However, one of the limitations of this work is that the task used had significant working memory demands, and so the findings may not be specific to sustained attention.

Indeed, one of the challenges of investigating sustained attention is the large number of possible confounds. Paradigms that selectively test sustained attention are difficult to create, because participants need to pay attention to *something*, and this will inevitably introduce cognitive demands above and beyond simple sustained attention. Attempting to address this problem, Grahn and Manly (2012) isolated brain regions underlying sustained attention controlling for common confounds in vigilance research by identifying areas activated by both the SART and a continuous tone-counting task. By comparing different paradigms, they were able to investigate the neural correlates of sustained attention regardless of stimuli modality or inhibition requirements. They identified the inferior frontal operculum, the anterior cingulate (ACC), and the premotor cortex (with some evidence for greater activity on the right than the left) as core regions underlying sustained attention.

Although vigilance research is defined by a decline in performance over time, relatively few neuroimaging studies have directly investigated the effect of time-on-task on brain activity (possibly due to the extremely long task lengths required to investigate vigilance decrement). The studies that required participants to maintain their attention for over 10 minutes have consistently found a decrease in brain activity over time, in line with behavioural findings (e.g., Breckel et al., 2011; Coull et al., 1998; Lim et al., 2010; Paus et al., 1997; Tana et al., 2010).

This decrease in activity is contrary to Langner and Eickhoff's (2013) findings. In their meta-analysis, they identified many regions that showed an increase in activity with greater time-on-task, but no regions associated with a decrease in activity over time. This discrepancy was likely due to the fact only 3 of the 55 studies included in their analysis

required participants to maintain attention for at least 10 minutes, while 47 of the studies included had periods of “sustained attention” lasting less than 120 seconds.

Observed declines in brain activity over time has been attributed to either a shift from controlled to automatic processing (e.g., Paus et al., 1997; Tana et al., 2010) or depletion of cognitive resources (e.g., Langner & Eickhoff, 2013; Lim et al., 2010). Of the studies investigating the time on task effect, Lim and colleagues (2010) also assessed patterns of brain activity predictive of better performance (lower vigilance decrement) using arterial spin labeling perfusion fMRI. When comparing pre-task and post-task baseline activity, better performance (in terms of less RT decline over time) correlated with a smaller decrease in cerebral blood flow in the right middle frontal gyrus, right inferior parietal lobule (IPL), and ACC. However, changes in brain activation during the task itself were not directly correlated with performance. The authors believe this may be due to the noise created by both transient and sustained patterns of blood flow taking place simultaneously during the task (Lim et al., 2010).

Finally, neuropsychological patient studies largely support the role of this frontoparietal network in sustaining attention. Patients with right frontal lesions (e.g., Alexander et al., 2005; Koski & Petrides, 2001; Molenberghs et al., 2009; Rueckert & Grafman, 1996; Shallice, Stuss, Alexander, et al., 2008; Wilkins et al., 1987), right parietal lesions (e.g., Malhotra et al., 2009; Rueckert & Grafman, 1998) or lesions in both these regions (e.g., Mennemeier et al., 1994), show reliable sustained attention deficits. There is particularly compelling evidence for the involvement of the right frontal region (see Koski & Petrides, 2001; Molenberghs et al., 2009). However, attentional deficits are common in most forms of brain injury, making precise interpretation of lesion data challenging

(Parasuraman et al., 1991). Indeed, patients with diffuse damage due to traumatic brain injury make more mistakes on the SART, particularly under low-challenge conditions (Manly et al., 2003). Many clinical disorders also lead to disruptions in sustained attention, including schizophrenia (e.g., Chen & Faraone, 2000; Liu et al., 2002), bipolar disorder (e.g., Bora et al., 2006; Clark et al., 2002; Maalouf et al., 2010), Alzheimer's disease (e.g., Baddeley et al., 2001; Berardi et al., 2005; Perry & Hodges, 1999), epilepsy (e.g., Fleck et al., 2002; Hernandez et al., 2003; Maneshi et al., 2012) and attention deficit hyperactivity disorder (ADHD; e.g., Barkley, 1997; Bellgrove et al., 2006; Manly et al., 2001; Rubia et al., 2009).

### **Task Switching**

Task switching, also referred to as “cognitive flexibility” or “set-shifting,” is a multidimensional process that involves the marshalling of cognitive resources to change tasks (Monsell, 2003). It includes the ability to disengage from a task and shift mental resources to a new goal. This transient, in-the-moment process is known as “local” task switching (Kiesel et al., 2010). Rather than maintaining focus, this aspect of task switching is concerned with the reallocation of attention. Understanding task switching has become increasingly relevant, given the rise in multi-tasking and constant context-switching between multiple channels of information across numerous devices. The ability to shift attention is also a key component of most models of executive functioning (e.g., Diamond, 2013; Miyake et al., 2000; Niendam et al., 2012; Stuss & Alexander, 2007).

### ***Task Switching Tasks***

Jersild (1927) conducted early research on switching and developed the first task switching paradigm. He was the first to describe the additional time it took for participants

to complete a block of trials when they were alternating between different tasks rather than performing a single task. However, this early approach confounded mixing and switching costs (see below). Researchers developed other strategies to investigate task switching, such as the “alternating runs” paradigm, where participants switch tasks at a constant and predictable rate (e.g., Rogers & Monsell, 1995). Another is the “task-cueing” paradigm, where switches are unpredictable, and a cue is presented to specify which task to perform (e.g., Sudevan & Taylor, 1987). These new paradigms allowed for the comparison of switch and repeat trials, as well as the manipulation of preparation effects (Monsell, 2003). In addition to these switching paradigms, one of the most popular neuropsychological assessments of mental flexibility is the Wisconsin Card Sorting Task (WCST). Developed by Grant and Berg in 1948, the task was designed to measure abstract reasoning and “shift of set.” The task requires participants to match cards and adapt their strategy based on the feedback they receive. After the participant performs ten correct matches, the rule covertly shifts, and the participants must adopt a new matching strategy. Performance on the WCST is sensitive to frontal lobe damage and executive dysfunction. Such patients show perseveration of response despite continued negative feedback, implying a diminished ability to shift task set (Buchsbaum et al., 2005; Demakis, 2003; Milner, 1963).

There have been many behavioural and imaging-based task switching studies in the last three decades, with a wide variety of tasks and types of switches. In their meta-analysis of neuroimaging studies of shifting, Wager and his colleagues (2004) identified five different types of switching abilities investigated in the literature. The first, “location switch,” requires participants to move their attention to a different spatial location. The second, “attribute switch” occurs when the critical feature of the stimuli changes (e.g., the

participant must now attend to colour rather than shape). The third, “rule switch,” involves the reorganization of stimulus-response mapping (e.g., whereas a participant was responding to a square with a left button press, they must now respond with a right button press). The fourth, “object switch” occurs when the stimulus itself changes. Finally, the fifth, “task switch,” occurs when the response set or the rule applied to the stimuli changes. The categories are exhaustive and Wager et al. acknowledge that under this classification many task switching paradigms involved many different types of switches at once. Alternatively, a trichotomous classification of switch types has been proposed (Kim et al., 2012). This includes “perceptual switches,” where the attended-to feature of the stimuli switches, “response switches,” where the stimulus-response mapping switches, and “context switches,” where the rule or the “set” switches (such as the WCST). Despite the many types of switches defined in the literature, all task switching paradigms were designed to investigate the cognitive ability of shifting from one goal to another. Switch cost is the observable and measurable expression of this process.

### ***Switch Cost***

The behavioural measure of task switching consists of a slower response or a more error-prone response on trials immediately following a switch. This decline in performance is termed “switch cost” (Dove et al., 2000; Monsell, 2003; Rubin & Miran, 2005). The difference in performance between switch trials (immediately after a task changes) and non-switch trials (when a task is repeated) is a measure of the increased cognitive effort required to shift tasks. Switch cost is distinct from mixing cost. Mixing cost is the performance cost associated with alternating between tasks compared to performing a task when no cognitive shifting is required. Mixing cost is calculated by comparing non-switch

trials within a “mixed block” against trials within a non-mixed, single-task block (Rubin & Meiran, 2005). While mixing cost captures the additional processing involved with performing tasks in a variable context, switching cost specifically assesses the process of shifting from one task to another.

Switch cost is a robust phenomenon, found across a variety of switching paradigms and experimental manipulations. In experiments that use a task cue, it is possible to manipulate the cue-to-stimulus interval to allow for additional preparation. Although longer preparatory periods lead to performance benefits, anticipatory preparation is not sufficient to entirely eliminate switch costs (Meiran et al., 2000; Monsell, 2003; Ruge et al., 2013). Moreover, when no cue is present, and the switch is predictable (as in an alternating-runs paradigm), participants nonetheless demonstrate a robust switch cost (Kimburg et al., 2000). These findings suggest that the cognitive process of shifting occurs regardless of preparation, predictability, or difficulty.

### ***Neural Substrates of Task Switching***

Multiple studies have investigated the neural basis of task switching. Meta-analyses of these studies (e.g., Buchsbaum et al., 2005; Kim et al., 2012; Wager et al., 2004) show a consistent pattern of brain activity associated with switching that relies on the superior medial PFC (smPFC), dorsolateral PFC (dlPFC), the insular cortex, and the posterior parietal cortex. One meta-analysis revealed no regions exclusively recruited by only one type of switching, supporting the view that multiple types of switches rely on a common neural network (Wager et al., 2004). Areas commonly recruited by all types of switching include the left inferior frontal junction and the left posterior parietal cortex (Kim et al., 2012). Several studies on task switching observe greater recruitment of the left hemisphere

(e.g., Braver et al., 2003; Kim et al., 2012; Ravizza & Carter, 2008). Braver and colleagues (2003) argue that the left-lateralization of task switching activity reflects the semantic classification of the tasks when a switch takes place. Many authors agree that the dlPFC activity seen during task switching is related to the maintenance of task-set and task-related goals, particularly in the presence of working memory demands (Braver et al., 2003; Kim et al., 2012; Ruge et al., 2013). Parietal activity has been associated with the reallocation of attention to the new task (Braver et al., 2003; Ruge et al., 2013). One study found that rule switching and perceptual switching preferentially engage different areas (Ravizza & Carter, 2008). Rule switches selectively recruited the dlPFC, in line with the hypothesis that this area is responsible for the maintenance of task-related goals. Perceptual switches recruited the superior parietal lobule (SPL), consistent with this area's role in the reallocation of attention.

Neuropsychological Studies have also investigated task switching in the context of focal brain injury. Studies have consistently shown that patients with lesions of the left lateral frontal lobes show a deficit in the top-down control of task-set and so exhibit increased switching costs (Aron et al., 2004; Mayr et al., 2006; Mecklinger et al., 1999). However, in a large patient sample, Shallice and colleagues found that those with smPFC lesions exhibited the greatest switch cost increase of any PFC lesion patient group (Shallice, Stuss, Picton, et al., 2008b). Although they acknowledge the critical importance of the left lateral PFC for “task-setting” (Shallice, Stuss, Picton, et al., 2008a), they point out the multi-dimensional nature of switching paradigms means that any lesion in the PFC is likely to disrupt typical task switching performance. Therefore, it is also not surprising that task switching is affected in several disorders such as ADHD (e.g., Cepeda et al.,

2000), Obsessive-Compulsive Disorder (OCD; e.g., Gu et al., 2007), unipolar depression (e.g., Meiran et al., 2011), and Parkinson's disease (e.g., Cameron et al., 2010; Woodward et al., 2002).

### **Two sides of the same coin?**

On the one hand, unitary models of executive control (e.g., Botvinick et al., 2001; Braver et al., 2009; Duncan et al., 2000; Duncan & Owen, 2000; Niendam et al., 2012) would predict that both the maintenance of attention on a given task and the shifting of attention to a different task rely on the same cognitive control system. These authors argue that a domain-general process (and a corresponding set of brain areas) underlie the majority of goal-directed cognition. In a neuroimaging meta-analysis of executive functioning, Niendam et al. (2012) included both switching and vigilance (in addition to initiation, inhibition, planning, and working memory) in their conceptualization of executive functioning. Unfortunately, they were unable to include vigilance data in their conjunction analysis of various executive tasks due to a lack of suitable studies. They were, therefore, unable to explicitly show the predicted overlap between vigilance and other executive functions, including switching tasks.

Nonetheless, the findings of Niendam et al. (2012) support the idea of a superordinate cognitive control network. This notion of superordinate control is similar to the view of Duncan et al. that the lateral PFC, recruited by diverse cognitive demands, is the basis of general intelligence (Duncan et al., 2000; Duncan & Owen, 2000), later identified as the "Multiple Demand System" (Duncan et al., 2010). Superordinate control is also compatible with the "Guided Activation Framework," which describes how top-down signals from the lateral PFC exert cognitive control throughout the brain (Cole et al.,

2013; Miller & Cohen 2001). One study provided preliminary support for this unitary view of attentional control when they found that both shifting and maintenance of simple visual attention recruited similar brain areas (Ikkai & Curtis, 2008).

Recently, functional connectivity research has provided additional evidence for a domain-general system, responsible for the voluntary control of attention. This network of brain regions is commonly labeled the frontoparietal control network, or FPCN (e.g., Power et al., 2011; Spreng et al., 2013; Vincent et al., 2008; Yeo et al., 2011). This unitary view of cognitive control is also compatible with some models of attention as well, such as the Large-Scale Distributed Network of Attention (Mesulam 1981, 1990, 1999) and the Supervisory Attentional System (SAS; Norman & Shallice, 1986; Shallice et al., 2008; Stuss et al., 1995; Stuss et al., 2002). In their 1995 paper, Stuss and colleagues outlined explicitly how the supervisory system controls both sustaining attention and switching attention and identified the lateral PFC as the core neurobiological substrate of the SAS.

### **Functionally Independent Processes?**

Alternatively, there is a large body of literature that would predict that sustained attention and task switching likely rely on separate cognitive mechanisms and neural networks in the human brain. First, a review of the neuroimaging literature for both these processes reveals different areas of BOLD activation, particularly in terms of lateralization (vigilance: left < right; task switching: left > right). Second, analogous to the literature that supports a unitary view described above, there is a body of literature that argues that these are independent processes. Existing models of attention (e.g., Corbetta et al., 2008; Corbetta & Shulman, 2002; Posner & Peterson, 1990; Peterson & Posner, 2012; Posner & Rothbart, 2007) and models of executive control (e.g., Dosenbach et al., 2007, 2008)

provide a framework for a non-unitary view of attentional control. We review these models and their predictions here.

Posner and Petersen's model of attention (Posner & Petersen, 1990; Posner & Rothbart, 2007) distinguishes three attentional processes, each with distinct anatomical networks and chemical modulators. The three networks are: (i) the "alerting network," responsible for maintaining vigilance, (ii) the "orienting network," which aligns attention with sensory signals, and (iii) the "executive network," which controls the top-down allocation of attention, particularly in the face of interference or conflict (Petersen & Posner, 2012; Posner & Rothbart, 2007; Raz & Buhle, 2006). In contrast to the SAS mentioned above, this model would predict that sustained attention and task switching are separable attentional processes that rely on distinct networks. Within this framework, vigilance is the domain of the alerting network, while the executive network controls task switching. At the neuroanatomical level, the alerting system is associated with the thalamo-frontoparietal network, similar to the regions identified in the sustained attention literature. This system also includes the locus coeruleus and relies on noradrenergic signaling, as opposed to the cholinergic system described in the sustained attention literature (e.g. Sarter et al., 2001). The executive system depends on the basal ganglia, the ACC, and undefined "frontal areas," and relies on dopaminergic signaling (Posner & Rothbart, 2007).

Corbetta and Shulman's endogenous vs. exogenous theory of attention (Corbetta & Shulman, 2002; Corbetta et al., 2008) also predicts that sustaining attention relies on a separate neural network than shifting attention. In this model, the dorsal attentional system, which consists of the intra-parietal cortex and superior frontal cortex, is responsible for the endogenous control of attention. This system therefore most closely resembles Posner and

Petersen's proposed "executive network." On the other hand, the ventral attentional system, composed of a right-lateralized network of ventral parieto-frontal regions, is responsible for exogenous and bottom-up control of attention. This system acts as a circuit breaker for the dorsal system and redirects focus when important or surprising stimuli are detected. In their original view, the authors argue that task switching, relying on top-down signals relating to task-set, is controlled by the dorsal system (particularly by the left posterior parietal lobe). In contrast, vigilance, which involves directing attention to a stimulus, relies on the ventral system (Corbetta & Shulman, 2002). However, in the 2008 revision of their model, they flip this prediction, indicating that the sustained focus on a task is the domain of the top-down dorsal network, while the transient and the cue-driven activity related with shifting attention relies on the ventral system (Corbetta et al., 2008). Although the predicted network affiliations are inconsistent between revisions to the model, the dorsal and ventral network view of attention holds that vigilance and task switching (or at least their component processes) are dissociable and rely on distinct networks.

Finally, an innovative approach to fMRI data analysis has allowed for the isolation of transient and sustained aspects of cognitive control (mixed block and event-related design: Donaldson et al., 2001; Konishi et al., 2001; Visscher et al., 2003). Although the "sustained" component of these types of studies is quite short (between 30 and 120 seconds), this line of research has led to the development of a dual-network model of executive control (Dosenbach et al., 2007, 2008). In this model, the frontoparietal network supports adaptive control on a moment-to-moment basis, while the cingulo-opercular network is responsible for "task-set maintenance" over the entire period of task performance. This model would predict that sustained attention would rely on the cingulo-

opercular network, composed of the anterior PFC, dorsal ACC, anterior insula, and the thalamus (although activity in this network has yet to be investigated during periods long enough to elicit an observable vigilance decrement). On the other hand, local task switching, a transient process, would be controlled primarily by the frontoparietal network, composed of the dlPFC, precuneus, IPL, intraparietal sulcus, and the mid-cingulate. One study has used a mixed design analysis to investigate sustained and transient brain activity in the context of a switching paradigm (Braver et al., 2003). Consistent with the dual-network model, they observed sustained activity in the anterior and lateral PFC, which they hypothesized represented the maintenance of a state of flexible cognitive control and task-set information. In contrast, they suggested that the left superior parietal cortex was responsible for the reconfiguration of the task-set in the moments following a switch.

### **Studies Comparing Sustained Attention and Task Switching**

Very few studies have examined both sustained attention and task switching. One study has investigated the neural basis of fixation and shifting of visual attention and found that the same regions (including precentral sulcus, inferior frontal sulcus, supplementary eye field, and intraparietal sulcus) were active in both conditions (Ikkai & Curtis, 2008). This work focused on the control of visual gaze, rather than the control of complex, goal-directed attention. Maintenance of visual attention was also limited to 13.5 seconds, which is well below the timeframes used in standard assessments of vigilance. Neuroimaging studies of task switching that use a blocked design have compared sustained periods of focus on a single task to sustained periods of task shifting (e.g., DiGirolamo et al., 2001; Dreher et al., 2002; Sylvester et al., 2003). These studies do not identify regions that are exclusively recruited by periods of switching. Rather, periods of task switching are

associated with further recruitment of the same regions identified in the single-task conditions (Ruge et al., 2013), which would support a unitary view of attentional control. However, these experiments were not designed to test sustained attention, so we must interpret these results with caution. As reviewed above, the work that led to the development of the dual-network model of executive control (e.g., Dosenbach et al., 2007, 2008) contrasted transient and sustained aspects of goal-directed attention. Nonetheless, it is difficult to apply these findings to our current question. For one, the periods of task set maintenance are too short to allow observable vigilance decrement and individual differences in attention span to emerge. These original studies also did not include task switching tasks in their design. One mixed-design study did look at the transient and sustained activity related to task switching specifically (Braver et al., 2003), but did not also examine sustained attention. Non-switch blocks were short (140 seconds) and made up of semantic classification tasks too complex to isolate brain activity associated with vigilance. As such, the relationship between sustained attention and task switching as yet to be directly, empirically tested.

### **The Present Study**

Gruber and Goschke (2004) describe the tension between the ability to maintain intentional and sustained focus and the ability to flexibly shift between tasks as a fundamental dilemma of cognitive control. However fundamental, this dilemma has remained under-explored. Reviewing the neuroimaging literature on both sustained attention and task switching throws into relief the differences between both processes. The right-lateralized network identified in the vigilance literature stands in contrast to the mostly left-lateralized patterns of activity found in task switching studies. Yet, no studies

to date have directly investigated whether sustained attention and task switching are dissociable abilities with different neural substrates. The current work set out to address these gaps in the literature. Here, we present a comprehensive examination of the relationship between the sustaining and shifting of goal-directed focus. We conducted a large-scale study of behavioural performance on cognitive tasks designed to test both abilities. To test sustained attention, we used tasks that adequately taxed the abilities of participants, with durations long enough to elicit vigilance decrement (Ballard, 1996). To test task switching, we used established paradigms that represent various types of switches (Kim et al., 2012). We also carried out a within-subjects neuroimaging study to directly investigate the neural correlates of these two abilities.

### ***Hypotheses***

Though the existing literature offers support for both possibilities, the balance of evidence suggests that the sustaining and shifting of attention likely depend on distinct cognitive and neural processes. We predicted: (1) behavioural performance on tasks of sustained attention and task switching would be dissociable, and (2) sustained attention and task switching would show distinct patterns of brain activity, with some areas of overlap in the lateral PFC and IPL. The individual studies designed to address these questions are described below.

## **Methods**

### **Confirmatory Factor Analysis Study**

To examine the relationship between sustained attention and task switching, we collected behavioural data aimed at estimating these two abilities. We conducted a confirmatory factor analysis of participants' performance on three sustained attention and

three task switching tasks. We aimed to determine whether performance on these tasks was best represented by a single-factor model, as would be predicted by a unitary model of attentional control, or by a dual-factor model, as would be expected if these processes were independent.

### ***Participants***

Three hundred participants were recruited through York University's Undergraduate Research Participant Pool and were offered course credit for their participation. They completed our behavioural test battery in return for course credit. Participants were healthy, right-handed, younger adults between the ages of 18 and 30 years, with no history of psychiatric or neurological conditions. The experimental design followed the guidelines of the Canadian Tri-Council's code of ethical conduct and was approved by the Institutional Review Board of York University.

Of the original 300 participants recruited into the study, the data from 44 participants were dropped due to technical difficulties during data collection, resulting in incomplete data sets or corrupted data files (demographic data for these 44 cases are unavailable). For the remaining 256 participants, we assessed performance on switching tasks to ensure task instructions were adequately followed. We excluded any individuals performing at or below chance (50% accuracy) on any switching tasks (12 cases: 10 women, 2 men,  $M_{\text{age}} = 19.25$ ,  $SD = 2.26$ , age range = 18-26 years). In addition to these cases, we also removed two additional outliers. The first outlier (20-year-old woman) had an unusually high error rate on repeat trials during the Number-Letter Task (NLT), described below (43% error rate: 20% higher [2.5  $SD$ s greater] than the next highest error rate on repeat trials). This participant also expressed an inverted pattern of performance

(more errors on repeat trials than switch trials). Although this inverse pattern of accuracy does occasionally occur, all other participants who expressed it had very low overall all error rates ( $< 10\%$ ), and so this participant was removed from the analysis. The second outlier (another 20-year-old woman) was excluded due to an unusually long median RT on repeat trials of the NLT (2009.5 ms), which was 633 ms (and 4.26 SDs) greater than the next longest median RT on repeat trials. All other cases were included in the analysis, for a total of 242 (159 women, 83 men,  $M_{\text{age}} = 19.93$ ,  $SD = 2.42$ , age range = 18-30 years).

### ***Experimental Tasks***

The behavioural test battery consisted of three sustained attention tasks (the SART, the CCPT, and a novel task named the Turner Sustained Attention Task or TSAT) and three shifting tasks (Number-Letter Task, Local-Global Task, and Visual Detection Task). With the exception of the TSAT, we selected these tasks because they are valid and established measures of either task switching or sustained attention. The TSAT (described below) was developed using the experimental procedure of the CCPT (Tsal et al., 2005) and matched to the visual design of the NLT (Rogers & Monsell, 1995). We designed this task to create a sustained attention task that could be directly compared to an established task switching paradigm (see neuroimaging study below). This also allowed us to include an additional sustained attention task that required a response on all trials (unlike the CCPT and the SART, which both require some form of response inhibition). We programmed all six tasks using E-prime 2.0 and administered them on a testing-dedicated Dell laptop. We conducted testing over a two-hour session in a designated behavioural testing room at York University. We counter-balanced the order in which the tasks were presented across participants, ensuring that no two tasks of task switching or sustained attention occurred

back-to-back (72 possible orders of task presentation). We also administered three questionnaires assessing language history, mind wandering, and social media use at the end of each session.

**Sustained attention.**

*Conjunctive Continuous Performance Test (CCPT)*. Developed by Tsal et al. (2005), the CCPT is a computer-based test that consists of a continuous presentation of standard geometric shapes of different colours. Participants were required to respond only to the target stimuli (a red square), and not to other stimuli. There were 16 different possible stimuli - all possible combinations of four standard geometric shapes (square, triangle, circle, and star) and four colours (red, green, blue, and yellow). The stimuli were presented in a random order for 100 ms and separated by an inter-stimulus interval (ISI) of 1,000, 1,500, 2,000, or 2,500 ms. There were 320 trials, and the target stimuli (the red square) appeared on 30% of all trials. Participants were to respond to the target as soon as it appeared on the screen by pressing the number “1” key (there is no required button press for all other non-target stimuli). A non-red square and a red non-square were presented in 17.5% of all trials, each. In the remaining 35% of the trials, a non-red, non-square stimulus was presented. A practice period of 15 trials preceded the CCPT. We instructed participants to respond with speed and accuracy. The CCPT lasted for a total of 10 minutes and allowed us to calculate both RT and accuracy scores for target trials. See Figure 1 for the task design of the CCPT.

*Sustained Attention to Response Task (SART)*. Developed by Robertson et al. (1997), the SART is a computer-based test where a single digit (2-9) is presented on each trial. Unlike the CCPT, participants are to respond with a simple button press to all

presented stimuli, except for a target digit (“3”). There were 225 trials (each possible digit was presented 25 times, representing 11% of total trials). The digits were displayed for 250 ms, in a pre-determined random order, followed by an ISI of 900 ms (a fixation cross was shown during the ISI). The SART lasted 5 minutes. A practice period of 18 trials preceded each session. We instructed participants to answer with speed and accuracy. The SART error rate was defined as the number of times participants failed to withhold their response to the target stimuli. See Figure 1 for the task design of the SART.

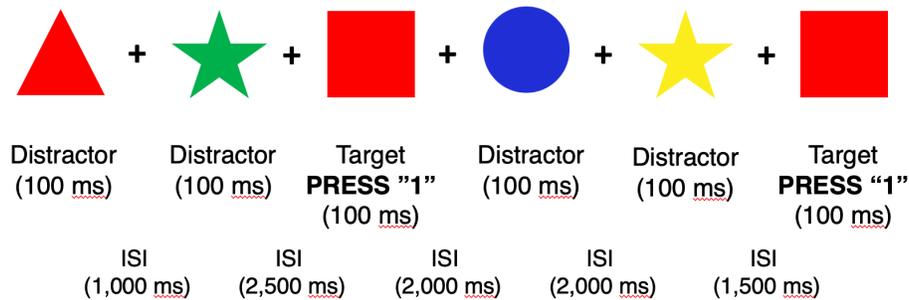
***Turner Sustained Attention Task (TSAT).*** This novel task is conceptually similar to the CCPT but matches the visual design of the NLT (Rogers & Monsell, 1995; see below). The stimulus, a number-letter pair (e.g., “A3”), was presented in a predictable clockwise fashion across four quadrants on the screen. We used combinations of eight letters (i.e., G, K, M, R, A, E, I, and U) and eight numbers (i.e., 2, 3, 4, 5, 6, 7, 8, and 9) to make a total of 64 unique stimuli. Stimuli were presented randomly for 200 ms with an ISI of 1,000, 1,500, 2,000, or 2,500 ms. We randomly selected a target number-letter pair for each participant. We instructed participants to respond by pressing the number “1” key when they saw the target pair (e.g., “U4”), and pressing the number “2” key for all other non-target pairs. Participants completed a single test block of 320 trials, with the target number-letter pair presented on 30% of trials. 17.5% of all trials displayed lure stimuli with the target letter, and another 17.5% displayed lure stimuli with the target number. The remaining 35% of trials displayed stimuli with neither the letter or number from the target pair. We gave participants 16 practice trials before the TSAT, and we instructed participants to respond with speed and accuracy. The duration of the TSAT was 10 minutes. We measured RT and accuracy for both target and non-target trials, and performance was

assessed over time to examine vigilance decrement. See Figure 2 for the experimental design of the TSAT.

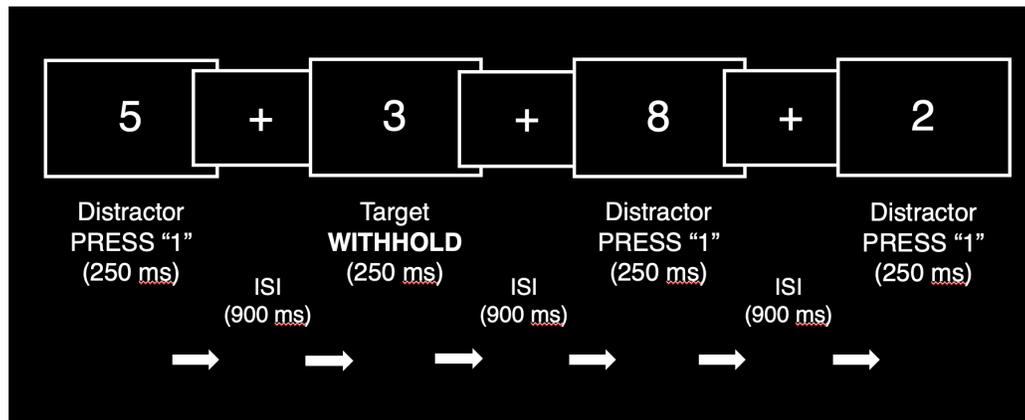
**Figure 1**

*Task Designs for Sustained Attention Tasks: CCPT & SART*

A.



B.



*Note.* A. Task design of the CCPT, based on Shalev et al. (2011). Participants only respond on target trials (red square). B. Task design of the SART, based on Robertson et al. (1997). Participants respond on all trials, except target trials ("3").

**Figure 2**

*Task Design for the Behavioural Study Version of the TSAT*



*Note.* In this example, “U4” is the target pair. This novel measure was derived from the experimental procedure of the CCPT (Shalev et al., 2011) and matched to the visual design of the Number-Letter Task (Rogers & Monsell, 1995).

### **Task switching.**

**Local-Global Task.** We adapted the Local-Global Task (LGT) from Miyake et al. (2000) and Leunissen et al. (2014). In this paradigm, a “global” figure (a large square or rectangle), made up of smaller squares or rectangles (“local” figures), was presented on the screen. A priming cue preceded each trial, indicating the dimension to which the participant should attend (either “local,” meaning the small individual figures, or “global,” meaning the large overall figure). A large square and rectangle on either side of the stimulus array

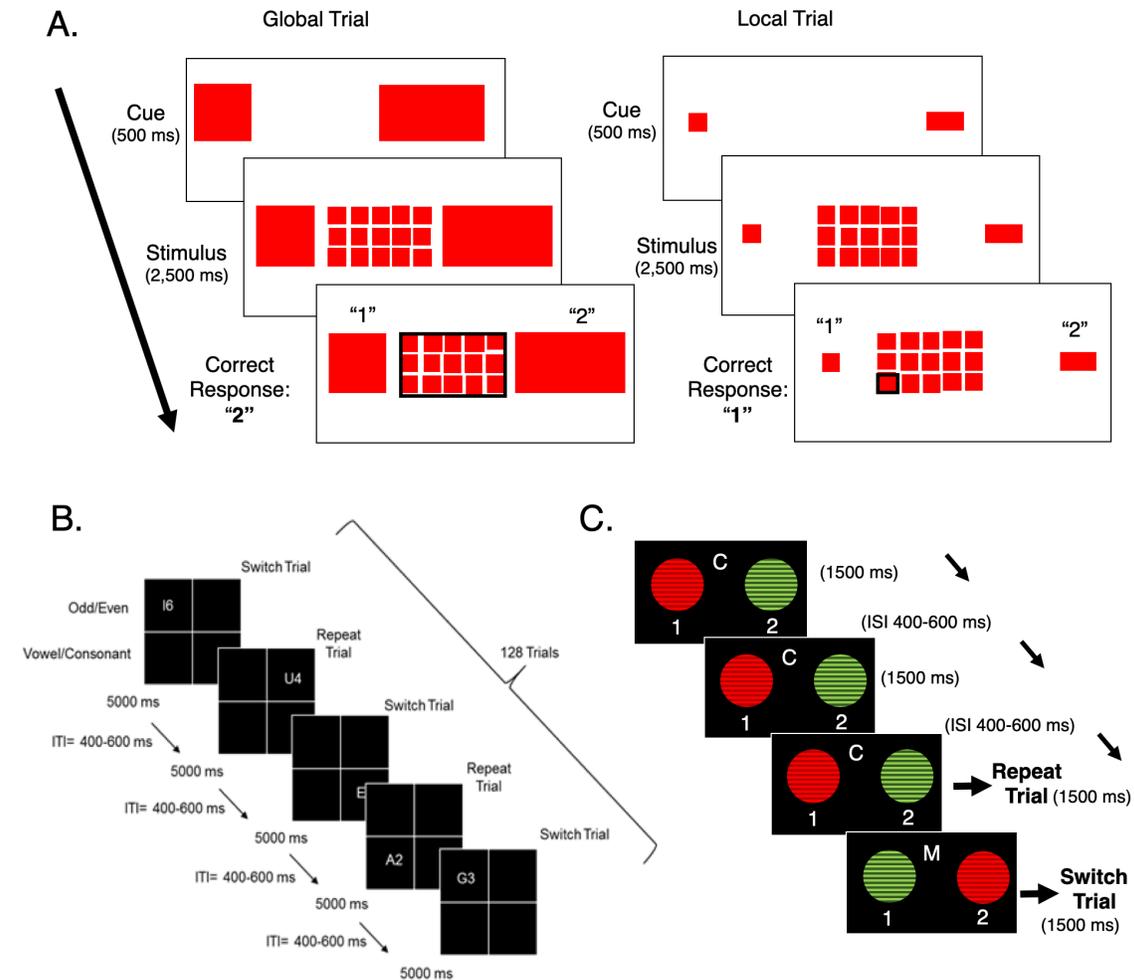
cued the participant to judge the “global” figure. A small square and small rectangle on either side of the stimulus array cued the participant to judge the “local” figure. See Figure 3 for task design. After a cue-stimulus interval of 500ms, the stimulus figure appeared. Both the cue and the target remained on the screen until the participant responded, or until 2,500 ms had elapsed. Participants were to identify the relevant target stimulus dimension by pressing “1” for squares and “2” for rectangles. The interval between participants’ responses and the beginning of the next trial was 1,000 ms. This task consisted of two non-switching blocks of 24 trials each (one “local-only” block and one “global-only” block). A “mixed block” of 49 trials followed, during which the target stimulus dimension alternated every other trial (i.e., two “local” trials, followed by two “global” trials). The timing of the switch was predictable, but not made explicit to the participants, as it is in the NLT (see below). Participants had the opportunity to practice both single-task and mixed-task blocks. Switch costs were calculated by comparing the accuracy between switch trials and repeat trials, as well as the RT difference between correct switch and correct repeat trials. All aspects of the task were identical to the experimental paradigm of Leunissen et al. (2014), with the exception of fixed rather than variable cue-target and inter-trial intervals.

***Number-Letter Task.*** Based on Rogers and Monsell’s task switching paradigm (1995), the NLT displayed number-letters pairs (e.g., “G6”) in one of four locations on a quadrant. See Figure 3 for task design. The location of successive stimuli was consistent and predictable, rotating across the quadrants in a clockwise manner. We instructed participants to attend to either the letter or the number in the pair, depending on the location of the stimuli. When the number-letter pair appeared in either of the top two quadrants, participants were asked to make an odd or even judgment about the letter (odd = 3, 5, 7, &

9; even = 2, 4, 6, & 8). When the number-letter pair appeared in either of the bottom two quadrants, participants were asked to make consonant or vowel judgment about the letter (consonant = G, K, M, & R; vowel = A, E, I, & U). There were three blocks, each preceded by 12 practice trials. During the first block (32 trials), stimuli appeared only in the top two quadrants (requiring only an even/odd judgment). During the second block (32 trials), stimuli were solely presented in the bottom two quadrants (requiring only a vowel/consonant judgment). In the third block (128 trials), stimuli appeared in all four quadrants, following a clockwise pattern. The number-letter pairs remained on the screen until the participant responded (for a maximum of 5000 ms). The ISI varied from 400-600 ms. Participants pressed the number “1” key to indicate vowels and odd numbers and pressed the number “2” key to indicate consonants and even numbers. The first two single-task blocks required no task switching. During the third “mixed” block, participants switched between the two tasks (number or letter judgment) every second trial. There were a total of 64 switch trials (trials immediately following a switch.) We calculated switch cost by comparing the RT on correct trials immediately following a switch (switch trials) to the RT on correct trials where no switch occurred (repeat trials).

***Visual Detection Task.*** We adapted the Visual Detection Task (VDT) from Liston et al. (2006). Two circular stimuli appeared side-by-side, one red and one green. Both stimuli had subtle stripes, which moved in a wave-like motion, either upwards or downwards across the stimuli. See Figure 3 for task design. Stimulus duration was 1,500 ms, and the ISI varied from 400-600 ms. A letter cue (“M” or “C”) appeared above the display to indicate which feature was relevant to the current trial: motion or colour. On “Colour” trials (“C” cue), participants were to indicate which of the two circles was red,

regardless of motion (“1” button press = left circle; “2” button press = right circle). On “motion” trials (“M” cue), they had to indicate which circle had upwards motion, regardless of the colour (“1” button press = left circle; “2” button press = right circle). Trials preceded by two to five trials of the opposite type were considered switch trials. Repeat trials were those preceded by two to five trials of the same type. The timing of the task switch was unpredictable. The task included three practice blocks, consisting of colour-only discriminations, motion-only discriminations, and alternating colour/motion discriminations, respectively (36 trials total). The participants then completed two blocks of 80 trials each, where the presentation of the stimuli and cues were pseudo-randomized (to ensure 20 switch trials per block). Consistent with Liston et al. (2006), we controlled the level of response conflict. In low response conflict trials, the red circle also had upward motion (and so the correct response was the same for both dimensions). In high response conflict trials, the red circle had downward motion, and the green circle had upward motion. The 40 switch trials in this task had balanced levels of response conflict. All parameters were identical to Liston and colleagues’ 2006 paradigm, with two exceptions: (i) we used a variable ISI rather than a fixed ISI of 500 ms and (ii) we presented the task in two blocks of 80 trials each, rather than 6 blocks of 72 trials each. Switch costs were calculated by comparing the accuracy between switch trials and repeat trials, as well as the RT difference between correct switch and correct repeat trials.

**Figure 3***Task Designs for Task Switching Tasks*

*Note.* A. Design of the Local-Global Task, based on Leunissen et al. (2014). B. Design of the Number-Letter Task, based on Rogers & Monsell (1995). C. Design of the Visual Detection Task, based on Liston et al. (2006).

**Other measures.** In addition to the tasks described above, we collected measures of bilingualism, mind wandering, and social media use, which will not be further discussed.

### *Data Analysis*

We carried out a series of confirmatory factor analyses (CFA) to assess whether unitary or fractionated models better accounted for the observed data. CFA is a theory-driven latent variable analysis technique, which allows for the evaluation of model fit given an a priori model and collected data. Descriptive statistics from all six tasks, as well as between-task correlations, were assessed across a number of different metrics to screen for outliers and select the best performance measures to include in the CFA analyses.

**Measures of interest.** Continuous performance tasks produce several measures that can assess sustained attention. Overall error rate, vigilance decrement, and response variability are all used in the literature as indices of attention (for reviews on the measurement of sustained attention using CPTs, see Esterman & Rothlein, 2019, and Riccio et al., 2002). We took into account several considerations in deciding which measure to include in our factor analyses. First, the design of SART precluded us from calculating reaction time measures for target trials, as correct responses on target trials required successfully withholding a response. We were, therefore, unable to calculate RT vigilance decrement or variability for target trials for this task. We calculated accuracy-based measure of vigilance decrement (e.g., 4<sup>th</sup> quartile vs. 1<sup>st</sup> quartile error rate) for each task, but found an inconsistent effect of time-on-task on accuracy. Indeed, the existing literature suggests that the SART and the CCPT do not show significant vigilance decrement in either reaction time or accuracy (Robertson et al., 1997; Shalev et al., 2011), likely due to their relatively short duration (Ballard, 1996). Ultimately, we determined that the overall error rate was the best measure to include in our analyses, as it was the primary measure of interest reported by the authors who originally designed these tasks (Robertson et al., 1997;

Shalev et al., 2011). It is also in keeping with established clinical neuropsychological measures of sustained attention, whose primary (though not only) performance measures are accuracy-based (e.g., Connor's CPT, Epstein et al., 1998; Ruff 2 & 7 Selective Attention Test: Ruff et al., 1992; Elevator Counting and Lottery subtests of the Test of Everyday Attention: Robertson et al., 1996). Finally, the overall error rate showed stronger correlations between sustained attention tasks than reaction time measures, lending further support to the use of error rate data in our models (see supplementary materials for correlation tables), as highly correlated indicators are preferable in confirmatory factor analysis (Little et al., 1999)

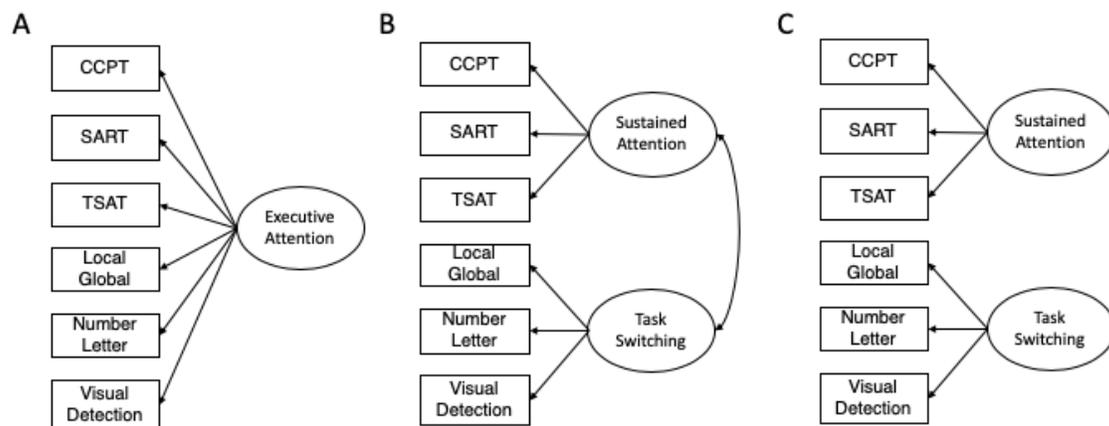
For consistency, we prioritized error rate data for measures of task switching as well. Both reaction time and accuracy differences between switch and repeat trials are used in the literature to measure switch cost (for reviews see Kiesel et al., 2010 and Monsell, 2003). As was the case with our sustained attention data, we found that error rate differences were more closely correlated between switching tasks than reaction time differences, confirming error rate was the better measure to use in factor analysis (Little et al., 1999). We, therefore, included error-rate differences between switch trials and repeat trials for all task switching tasks. See supplementary materials for correlations between different measures.

**Model estimation.** We carried out the analysis using lavaan version 0.6-5 (Rosseel, 2012) in the R statistical software package (version 3.6.1; R Core Team, 2013). Three models were estimated to evaluate the best fit for the data: (1) a one-factor model of attentional control, where performance on all six tasks load on a single factor, (2) a two-factor model of sustained attention and task switching, and (3) an orthogonal two-factor

model with no covariance between sustained attention and task switching (See Figure 4 for a diagram of the models tested). For all CFAs, we used robust maximum likelihood estimation. There were no missing data, and all variables were continuous. We standardized the latent factors by setting the latent variable variances to 1. This allowed the free estimation of all factor loadings, including corresponding  $p$ -values.

**Figure 4**

*Three CFA Models Estimated in the Behavioural Study*



*Note.* A. A one-factor model where performance on all task load onto a single factor representing executive control of attention. B. A two-factor model, where performance on different tasks load onto either a sustained attention factor or a task switching factor, and where these two factors are allowed to covary. C. An orthogonal two-factor model where task performance loads onto one of two factors, and where the two factors do not covary with each other.

**Model fit.** In addition to comparing conventional model-fit statistics, we directly compared the estimated models using the Scaled Chi-Squared Difference Test (Satorra & Bentler, 2001). Model-fit statistics compared in our analysis included the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), the Akaike Information Criterion (AIC), the root

mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). We followed established guidelines to interpret these statistics. For CFI and TLI scores, higher scores (i.e., higher than .90) are considered to reflect a better fit (Hu & Bentler, 1999). AIC is primarily used when directly comparing multiple models. It provides an approximation of information loss in estimated models, such that the best model is the one with the lowest AIC value (Symonds & Moussalli, 2011). For the RMSEA, a score less than .05 was considered a close fit, a score between .05-.10 considered an acceptable to mediocre fit, and anything larger considered a poor fit (Browne & Cudeck, 1993; MacCallum et al., 1996). For the SRMR, values below .08 are considered to be a close fit (Hu & Bentler, 1999).

**Power analysis and sample size.** Structural equation modeling allows us to explore complex associations across multiple sources of data. As such, conducting power analyses to determine a-priori sample sizes for structural equation modeling analyses such as CFA is more complex than it is for univariate research designs, as multiple parameters are estimated at once (MacCallum et al., 1999; Marsh et al., 1998; Westland, 2010; Wolf et al., 2013). Given this, there are several proposed heuristics to help determine a-priori sample size when conducting CFA: Boomsma (1982) recommends a minimum  $N$  of 200; Nunnally and Bernstein (1967) suggested that  $N/p \geq 10$  (where  $p$  is the number of indicators or manifest variables included in the model); Bentler & Chau (1987) as well as more recent works (e.g., Jackson, 2007; Schreiber et al., 2006) suggest  $N/q \geq 5-10$  (where  $q$  is the number of parameters to be estimated in the model).

Several authors have called into question the heuristic approach in determining sample size, highlighting the importance of the properties of the model in question instead

(e.g., Gagne & Hancock, 2006; Myers et al., 2011; Wolf et al., 2013). In general, higher  $p/q$  ratios are more likely to lead to well-identified models that successfully converge (Jackson, 2007; Marsh et al., 1998; Gagne & Hancock, 2006). Larger sample sizes and greater effect sizes (i.e., factor loadings in CFA) also increase the likelihood of convergence (Gagne & Hancock, 2006; Wolf et al., 2013). Using Monte Carlo analyses of various CFA models, a number of studies have identified the minimum number of participants needed under different model conditions. Gagne and Hancock (2006) tested model convergence under different  $p:f$  ratios (where  $f$  is the number of factors being estimated). For a ratio of 3 (the lowest  $p:f$  ratio in the current study), the minimum  $N$  was 50 for factor loadings of .80,  $N_{min} = 100$  for factor loadings of .60, and  $N_{min} = 400$  for factor loadings of .40. Wolf and colleagues (2013) investigated the effect of the number of factors and indicators included in a CFA model. For two-factor models with six-indicators (the design of the most complex model estimated in the current study), the minimum  $N$  was just under 200 (for a factor loading of .50 – the smallest effect size studied). Higher factor loadings required even smaller minimum sample sizes (e.g.,  $N_{min} = 100$  for a factor loading of .80).

Finally, we also ran an a-priori power analysis using Westland's 2010 algorithm (Soper, 2018; Westland, 2010) to determine the minimum necessary sample size. We considered the smallest effect sizes observed in Miyake et al. (2010), a similar CFA of executive functioning in undergraduate students, where the lowest factor loadings were .33. With an effect size = .33, an alpha = .05 and power = .80, the projected minimum sample size needed was  $N = 90$ . With a smaller effect size of .20, the projected minimum sample size needed was  $N = 223$ . Given this, our original sample size of 300 (as well as

our final sample size of 242) was more than adequate for the successful convergence of the models estimated in the current study. It also exceeded the minimal sample size suggested by the heuristics previously laid out in the literature: (1) our sample size was greater than 200; (2) in the current study,  $N/p \geq 10$  would dictate a minimum sample size of 60 (as we have six indicator variables); (3)  $N/q \geq 10$  would dictate a minimum  $N$  of 130 (as we estimate 13 parameters in our two-factor model).

### **Neuroimaging Study**

To complement our behavioral investigations we also examined whether sustained attention and task switching varied in their neural substrates, measured using functional MRI methods. Using multivariate approaches to the analysis of the neuroimaging data, we explored the relationship between the neural networks that underlie sustained attention and task switching. This series of experiments leveraged our carefully matched tasks (NLT-TSAT) and a within-subjects design to define brain regions critical to the sustaining and shifting of attention. We then conducted conjunction analyses to look for areas of overlap or divergence in the functional brain patterns associated with the two processes.

### ***Participants***

Twenty-five participants were recruited through York University's Undergraduate Research Participant Pool, flyers and word-of-mouth. Participants were financially compensated for their participation (\$50 CND). Participants had no reported history of psychiatric or neurological illnesses, did not suffer from claustrophobia, and had no ferromagnetic metal in their bodies. All participants completed an additional MRI screening procedure before participating in the study. The study followed the guidelines of

the Canadian Tri-Council's code of ethical conduct for research involving humans and was approved by the Institutional Review Board of York University.

Four participants (3 women, 1 man,  $M_{\text{age}} = 18.75$ ,  $SD = .96$ , age range: 18–20 years) were excluded from the analysis due to poor performance (scoring less than chance on the NLT while in the scanner), and an additional participant (24-year-old male) was excluded due to movement artifacts. This left 20 participants included the final analysis (12 women, 8 men,  $M_{\text{age}} = 19.33$ ,  $SD = 1.72$ , age range: 18–23 years, all right-handed).

### ***Experimental Procedure***

We adapted two of the six tasks used in the behavioural study for use in the MRI scanner. The tasks were designed to measure sustained attention and task switching, respectively. They were also carefully matched to control for non-attentional task demands, such as motor demands, predictability of stimuli location, and visual processing. These two tasks also had the highest factor loadings on their respective constructs in the factor analysis findings (see behavioural study results). To test sustained attention, we used our novel continuous performance task, the TSAT (based on the CCPT, Shalev et al., 2011; described above). To assess task switching, we used the NLT (Rogers & Monsell, 1995; described above). In both tasks, the display consisted of four quadrants. Both tasks used number-letter pairs as stimuli, appearing in a consistent and predictable location, in a clockwise order across all quadrants. Both tasks also required the participants to respond with a button press on every trial. See Figure 5 for task design. Tasks were programmed using E-prime 2.0 (runtime version 2.0.10.242, Psychology Software Tools, Inc.) and administered with the use of a testing-dedicated Dell laptop computer running windows 8. Before completing



distributed between all trials. Null trials accounted for one-third of the total scan time. We designed the tasks to allow for both blocked and event-related analyses. In the case of the TSAT, a fixation cross lasting at least 1,800 ms appeared after each stimulus. The fixation cross was jittered on one-third of the trials, where the duration of the fixation lasted 3,800, 5,800, or 7,800 ms. Participants had 2,000 ms to respond after stimulus onset. The total period of the TSAT was 11 minutes in length: 10 minutes of task (a total of 225 trials, with 68 target trials), bookended by the presentation of a fixation cross for 30 seconds at the beginning and end of the run.

As for the NLT, each number-letter pair was presented on the screen for 200 ms, followed by a fixation cross lasting at least 1,800 ms. The fixation cross was jittered on one-third of the trials, where the duration of the fixation cross lasted 3,800, 5,800, or 7,800 ms. Participants had 2,000 ms to respond after stimulus onset. A cue was left on the screen as a reminder of the rules (“number” written near the top of the screen, and “letter” written near the bottom of the screen) across all three blocks (letter-only, number-only, and mixed number-letter) to reduce working memory load. The total duration of the NLT was 9 minutes and 46 seconds: 8 minutes and 26 seconds of task, bookended by the presentation of a fixation cross for 30 seconds at the beginning and end of the run. A fixation cross was also displayed for ten seconds between blocks. For the current analyses, we focused on the last block (64 repeat trials and 64 switch trials, for a total of 128 trials).

### ***MRI Data Acquisition and Pre-Processing***

Participants were scanned using a Siemens 3T Magnetom Tim Trio MRI scanner at York University. Visual stimuli were back-projected on to a screen that the participants viewed through a mirror. Functional scans were acquired using a 32-channel head coil. We

used a T2\*- weighted 2D Echo Planar Images (EPI) sequence sensitive to BOLD contrast, acquired in the oblique-axial plane (36 axial slices, 3 mm iso, echo time = 30 ms, flip angle = 90°, field of view = 240 mm<sup>2</sup> with an 80 x 80 matrix size). Repetition time (TR) was 2000 ms. High-resolution 3D structural images were acquired using a T1-weighted sequence, multi-planar rapid gradient echo (MP-RAGE) (192 slices, 1 mm iso, repetition time = 1900 ms, echo time = 2.5 ms, TI = 900, flip angle = 9°, field of view = 256 mm<sup>2</sup>.) Over both functional runs, we collected a total of 623 scans (293 scans during the NLT and 330 during the TSAT). The data were pre-processed using Analysis of Functional Neuroimages software (AFNI; Cox, 1996). First, the data were de-spiked, removing any activity outliers and replacing them with smooth fitted curves. Next, we applied a slice-time correction to the data. Following this, the functional data were co-registered to the initial volume and motion corrected. We then smoothed the data using a Gaussian kernel of full-width at half-maximum of 6mm. Finally, we used a linear registration to transform all the data to Montreal Neurological Institute (MNI) coordinates. We also created whole-brain masks for each participant, co-registered to their anatomical image to limit analyses to brain space.

### ***fMRI Data Analysis***

The fMRI data were analyzed using Spatiotemporal Partial Least Squares (PLS; Krishnan et al., 2011; McIntosh et al., 1996). This multivariate, data-driven technique robustly identifies whole-brain, functionally covarying patterns of activity that are associated with the experimental design. Spatiotemporal PLS as a technique is sensitive to co-variations in distributed voxel responses, across time (Krishnan et al., 2011; McIntosh et al., 2004; Nichols & Hayasaka, 2003). As PLS is sensitive to covariance structure in the

brain data, the analysis technique makes no assumptions about the shape or duration of the hemodynamic response. Further, all voxel-wise calculations are performed in a single step, using singular value decomposition, therefore requiring no correction for multiple comparisons (McIntosh & Lobaugh, 2004; McIntosh et al., 2004).

**Mean-centred PLS.** The pre-processed neuroimaging data from both tasks were first analyzed separately using mean-centred PLS. This analysis operates on the covariance between brain voxels and experimental design to obtain a new set of variables that optimally relate the two sets of measurements. We created a data matrix using the experimental model, the event-onset times, and the BOLD response of each voxel at each time point. We then conducted singular value decomposition on the data matrix to identify significant patterns of activation (“latent variables” or LVs) in the data. As the decomposition of the entire data matrix is completed in a single mathematical step, there was no need to correct for multiple comparisons. LVs are composed of two vectors, one representing the task conditions most related to brain activity, and the second reflecting the optimal pattern of whole-brain activity related to aspects of the task conditions (McIntosh et al., 1996; McIntosh et al., 2004). LVs express the covariance between brain voxels and elements of the experimental design. Significant LVs represent patterns of BOLD activity covariance across the whole brain that are best explained by the study design (Krishnan et al., 2011; McIntosh et al., 1996). Each voxel has a weight (or “salience”), indicating the strength of the covariance between that voxel and a given LV. For each participant, across each LV and conditions, we obtained “brain scores” by multiplying salience by the BOLD signal for each voxel in the brain and summing across all voxels. The brain score is a representation of the degree to which each participant expressed the pattern of activity

identified by a given LV. We then averaged the brain scores across participants and applied 95% confidence intervals (obtained from the bootstrap analysis, see below). The average brain scores plot the extent to which the different patterns of activity identified by each LV are associated with the conditions included in the experimental design.

We used permutation testing to determine the statistical significance of identified LVs. By randomly reordering the data for each participant (resampling without replacement) 500 times, we were able to assess whether the effect in any identified LV is sufficiently strong to be different from random noise or artifacts (Krishnan et al., 2011). In a second, independent step, we calculated standard errors for the voxel saliences in each identified LVs using bootstrap estimation. This calculation allowed us to determine the reliability of non-zero brain saliences for all significant LVs and minimize the influence of outliers. The data were resampled with replacement 500 times, keeping the original assignment of the experimental conditions fixed for each participant. We assessed the reliability of each voxel by examining the ratio of its salience to its standard error (i.e., the “bootstrap ratio” or BSR). Clusters larger than 20 voxels with a BSR of at least  $\pm 3.3$  (approximately  $p < .001$ ) are reported. The local maximum represents the voxel with the greatest BSR value within a given cluster.

To capture the transient nature of local task switching, we analyzed the NLT data using an event-related design. We modeled repeat and switch trials from the final mixing block of the NLT. Event-related PLS provides a set of reliable brain activity patterns related to the task conditions at eight post-stimulus time points (i.e., 8 TRs = 16s). In the current study, the results focus on the second TR (i.e., 4s following trial onset). In selecting this TR, we attempted to balance the typical timing of the hemodynamic response function’s

peak (4–6s) with the potential contamination of subsequent trials (at 4s, there is a maximum of only one intervening trial). This is in line with previously published data by our research group (e.g., Lemire-Rodger et al., 2019). Further, this lag time was associated with the strongest correlations between brain scores and behavioural performance data in our behavioural analysis (see below).

To capture the continuous nature of sustained attention, we analyzed the TSAT data using a blocked design. We divided the data from the TSAT into five 2-minute epochs, each made up of a series of 10 consecutive “pseudo-blocks” lasting 6 TR (12 s). We based this approach on previous PLS-based work using continuous pseudo-blocks to model resting state data (e.g., Grigg & Grady, 2010) and optimizing block length to maximize continuous signal detection (Wang & Protzner, 2014, unpublished data).

**Behavioural PLS.** In addition to the mean-centred analysis described above, we also set out to examine how individual differences in performance affected the recruitment of key brain areas. To do this, we used behavioural PLS to identify brain regions in which task-related activity correlated with participant performance on the TSAT and the NLT (McIntosh et al., 2004; Krishnan et al., 2011). Specially, we looked at vigilance decrement (as measured by the difference in median reaction time between the first and last epochs of the TSAT) and switch cost (as measured by the difference in median reaction time between switch and repeat trials on the NLT). We ran two separate behavioural PLS analyses, one for each task. These analyses were similar to mean-centred PLS described above, only that the original data matrices were cross-correlated with the specified behavioural measures before undergoing singular value decomposition. This produced a new set of LVs that capture the similarities and differences in brain-behaviour relationships across the brain.

As with mean-centred PLS, we assessed statistical significance using permutation testing and reliability of voxel saliences using bootstrapping.

**Conjunction analysis.** Finally, to assess the overlap in the functional networks underlying the sustaining and shifting of attention, the resulting activation maps from these analyses were subjected to conjunction analyses. The results from the original mean-centred PLS analyses for the TSAT and the NLT (both thresholded at BSR of + 3.30) were overlaid and compared to identify regions of statistical overlap (using the 3dcalc program in AFNI; Cox, 1996). We repeated this procedure with the results of the behavioural PLS analyses.

## Results

### Confirmatory Factor Analysis Study

#### *Descriptive Statistics*

Descriptive statistics for error rate data are provided in Table 1 for sustained attention tasks, and Table 2 for task switching tasks. Visual inspection of the frequency distribution of error rates for sustained attention tasks revealed positively skewed data, due in part to ceiling effects, as many participants made no errors on target trials (particularly on the CCPT). To address this skewness, we applied a natural log transformation to the sustained attention error rate data ( $\ln[\text{error rate} + 1]$ ), and we carried out the factor analyses with both the original and transformed data. Ultimately, model fit statistics were better for the models estimated using the original data. We, therefore, present the results for the untransformed data here (model fit statistics for the transformed data are available in supplementary materials). We report zero-order correlations between overall error rates (for sustained attention tasks) and switch costs (for task switching tasks) in supplementary

materials (as well as equivalent median RT correlations for comparison). Correlation values ranged from .08 to .48, consistent with previous studies of individual differences on executive tasks (Miyake et al., 2000). Significant correlations were observed between most tasks, with the strongest correlations between tasks measuring the same construct ( $r = .18$  to .48, all  $p < .05$ ). The CCPT did not significantly correlate with any of the task switching measures, and the SART did not significantly covary with the VDT ( $r = .08$ ,  $p = .08$ ) (see supplementary material, Table I for full list of correlations).

**Table 1**

*Descriptive Statistics for Error Rate Data on Sustained Attention Tasks*

Task	<i>M</i> ( <i>SD</i> )	Min	1 <sup>st</sup> Qrt	2 <sup>nd</sup> Qrt	3 <sup>rd</sup> Qrt	Max
CCPT	2.80 (4.10)	0.00	0.00	1.04	3.13	28.13
SART	34.60 (21.73)	0.00	20.00	32.00	48.00	96.00
TSAT	12.85 (10.19)	0.00	5.21	10.42	17.45	53.13

*Note.* Error rate (percentage of incorrectly answered trials) on target trials.

**Table 2**

*Descriptive Statistics for Error Rate Data on Task Switching Tasks*

Task	Repeat trials ( <i>SD</i> )	Switch trials ( <i>SD</i> )	Switch cost ( <i>SD</i> )	Min	1 <sup>st</sup> Qrt	2 <sup>nd</sup> Qrt	3 <sup>rd</sup> Qrt	Max
LGT	6.63 (6.60)	9.92 (8.94)	3.27 (7.86)	-14.51	-2.26	2.53	6.95	40.00
NLT	3.93 (5.07)	9.36 (7.90)	5.43 (5.34)	-6.20	1.61	4.79	8.04	22.54
VDT	8.54 (6.79)	11.88 (8.38)	3.34 (7.47)	-14.76	-1.44	2.84	7.50	30.24

*Note.* Error rate (percentage of incorrectly answered trials) on repeat and switch trials, as well as switch cost (error rate difference between switch trials and repeat trials). Minimum, maximum, and quartile data reported for switch cost.

### ***Model Selection***

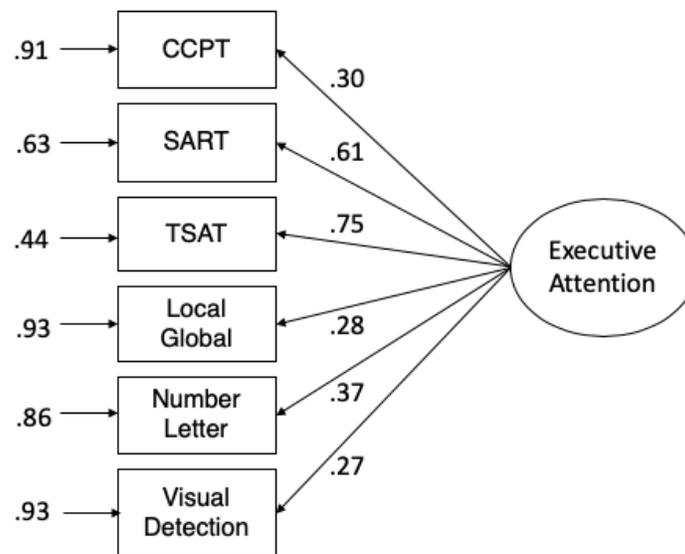
Estimated models, including standardized factor loadings and standard residual error variances, are shown in Figures 6-8. Fit indices for the three models are displayed in Table 3. Chi-square tests for the one-factor and two-factor model were non-significant, indicating that predicted covariance matrices were not significantly different than those obtained with the present data (one-factor:  $\chi^2(9) = 11.94, p = .22$ ; two-factor:  $\chi^2(8) = .82, p = .99$ ). The orthogonal two-factor model had a significant chi-square test, indicating that the predicted and obtained covariance matrices were significantly different, implying possible poor model fit ( $\chi^2(9) = 22.43, p < .01$ ). Model fit statistics suggest that the (non-orthogonal) two-factor model fits the data best. On all indices, the two-factor model was associated with better fit. Of the three models, the two-factor model had the lowest chi-square value ( $\chi^2(8) = .82, p = .99$ ), as well as the highest Comparative Fit Index (CFI = 1.00) and Tucker-Lewis Index (TLI = 1.14). The Akaike Information Criterion (AIC = 10086.82) was also lower for this model than both the one-factor and orthogonal two-factor model. The two-factor model had a RMSEA value of 0.00 ( $p = 1.00$ ), indicating a close fit to the data. The SRMR, an absolute measure of fit reflecting the mean value of the components of the residual covariance matrix, was 0.01 (well below the suggested cut off of .08; Hu & Bentler, 1999).

We also directly tested the estimated models against each other using the Scaled Chi-Squared Difference Test (Satorra & Bentler, 2001). The two-factor model, with sustained attention and task switching as the two latent factors, fit the data significantly better than the one-factor model representing general executive control of attention ( $\chi^2(1) = 15.84, p < .001$ ). This two-factor model, which allowed for covariance between the

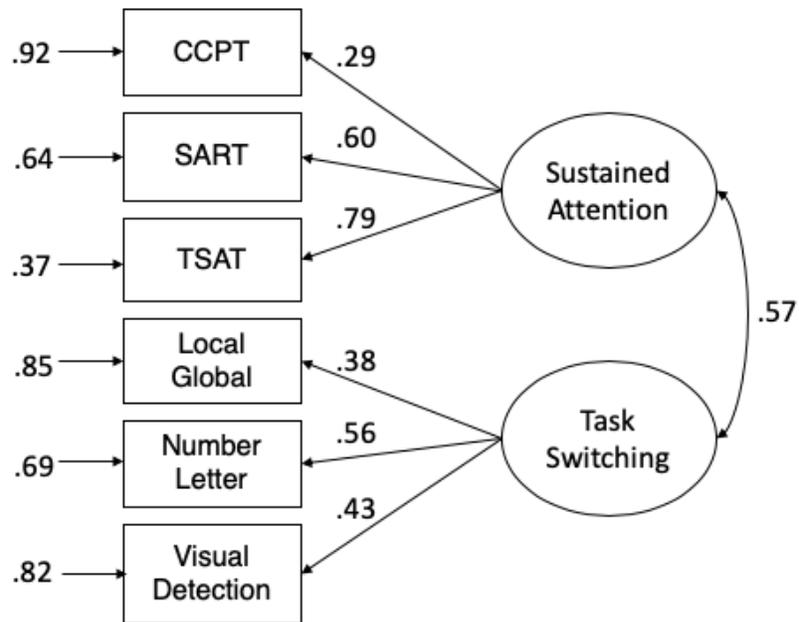
sustained attention and task switching factors, also fit the data significantly better than the orthogonal two-factor model, which treated the two factors as completely independent ( $\chi^2(1) = 22.72, p < .001$ ). In other words, the model where sustained attention and task switching were represented by two separate but related latent variables fit the data best.

**Figure 6**

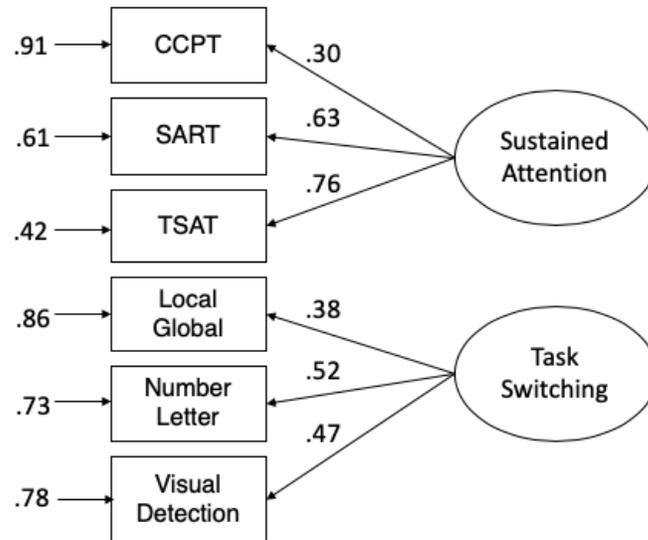
*Estimated One-Factor Model*



*Note.* Standardized factor loadings (equivalent to regression coefficients) are indicated next to the angled arrows. All factor loadings were significant at the  $p < .01$  level. Standardized residual variances associated with each variable are shown on the left.

**Figure 7***Estimated Two-Factor Model*

*Note.* Standardized factor loadings (equivalent to regression coefficients) are indicated next to the angled arrows. All factor loadings were significant at the  $p < .01$  level. Standardized residual variances associated with each variable are shown on the left.

**Figure 8***Estimated Orthogonal Two-Factor Model*

*Note.* The estimated orthogonal two-factor model. Standardized factor loadings (equivalent to regression coefficients) are indicated next to the angled arrows. All factor loadings were significant at the  $p < .01$  level. Standardized residual variances associated with each variable are shown on the left.

**Table 3***Fit Indices for Estimated CFA Models*

Model	$\chi^2$	df	Fit Indices				
			CFI	TLI	AIC	RMSEA	SRMR
One-factor	11.94	9	.97	.95	10097.02	.04	.05
Two-factor	0.82	8	1.00	1.14	10086.82	.00	.01
Orthogonal two-factor	22.43	9	.86	.76	10111.15	.08	.10

*Note.* *df* = degrees of freedom; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; AIC = Akaike's Information Criterion; SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation.

As expected, the indicators all showed significant positive factor loadings, with standardized coefficients ranging from .29 to .79 for the two-factor model (see Figure 7). For estimated models, all factor loadings were significant at the  $p < .01$  level. In the two-factor model, the sustained attention factor and the task switching factor significantly covaried with each other (standardized covariance: .57,  $p < .001$ ). Despite this model's excellent fit statistics, it is notable that the uniqueness estimates are large, with a relatively high range of variance that is not explained by the model for sustained attention (range: 37%-92%) and task switching (range: 69%-85%). These error variances, while high, are in line with other research findings in the cognitive literature (Miyake et al., 2000). Overall, our modeling provides strong evidence that performance on sustained attention and task switching tasks are distinct but related abilities.

## **Neuroimaging Study**

### ***Participant Performance***

On the TSAT, overall mean accuracy was 97.64% ( $SD = 2.52\%$ ). We did not observe a significant decrement in accuracy between the first and last epochs (paired-samples  $t(19) = 1.58$ ,  $p = .13$ ). The average of median RT on correct trials was 553.38 ms ( $SD = 69.97$  ms). Median RT was significantly longer during the last epoch when compared to the first epoch (paired-samples  $t(19) = -3.37$ ,  $p < 0.01$ ), representing observable vigilance decrement. Epoch-wise accuracy and reaction times are reported in Table 4. For the mixed block of the NLT, overall accuracy was 88.52% ( $SD = 5.82\%$ ). For correct trials, the average of median RT was 814.08 ms ( $SD = 211.88$ ). Accuracy and median RT data for repeat and switch trials are reported in Table 5. Statistically significant switch costs were

observed both in terms of accuracy (paired-samples  $t(19) = -6.35, p < .001$ ) and median RT (paired-sample  $t(19) = 7.97, p = .001$ ).

**Table 4**

*Mean (SD) Accuracy and Reaction Time Data for the TSAT*

	Epoch 1	Epoch 2	Epoch 3	Epoch 4	Epoch 5
Accuracy	97.89 (4.04)	99.56 (0.91)	98.00 (2.87)	97.33 (2.56)	95.44 (6.39)
Median RT	517.28 (64.52)	535.88 (68.01)	546.23 (81.41)	560.98 (79.33)	571.28 (83.20)

*Note.* Standard deviations in parentheses. Accuracy = % correct. Average of participants' median RT in ms.

**Table 5**

*Mean (SD) Accuracy and Reaction Time Data for the NLT*

	Repeat trials	Switch trials	Switch cost	<i>P</i> -value
Accuracy	92.27 (5.16)	84.77 (7.43)	7.5	<.001
Median RT	678.23 (103.94)	949.88 (206.21)	271.6	<.001

*Note.* Accuracy = % correct. Average of participants' median RT in ms.

***PLS Analyses***

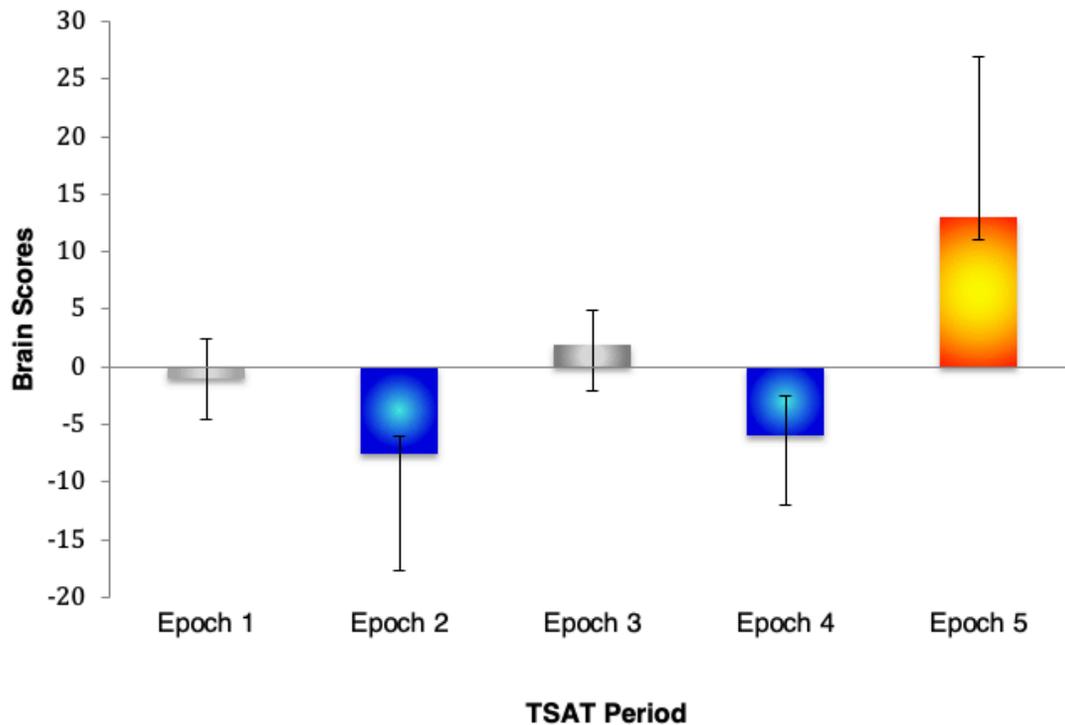
**Sustained attention.**

***Mean-centred analysis.*** The basic mean-centred analysis of the TSAT data revealed one significant LV ( $p < .05$ ), dissociating the final epoch from the others (namely the 2<sup>nd</sup> and 4<sup>th</sup> epochs) and accounting for 46.23% of the cross-block covariance in the data. Figure 9 represents the extent to which the identified pattern of brain activity is expressed (brain scores) in each condition (epochs). Figure 10 depicts the patterns of activity themselves, projected onto partially inflated brain surfaces using CARET software (Van Essen et al., 2001). The brain areas recruited during the majority of the duration of the task

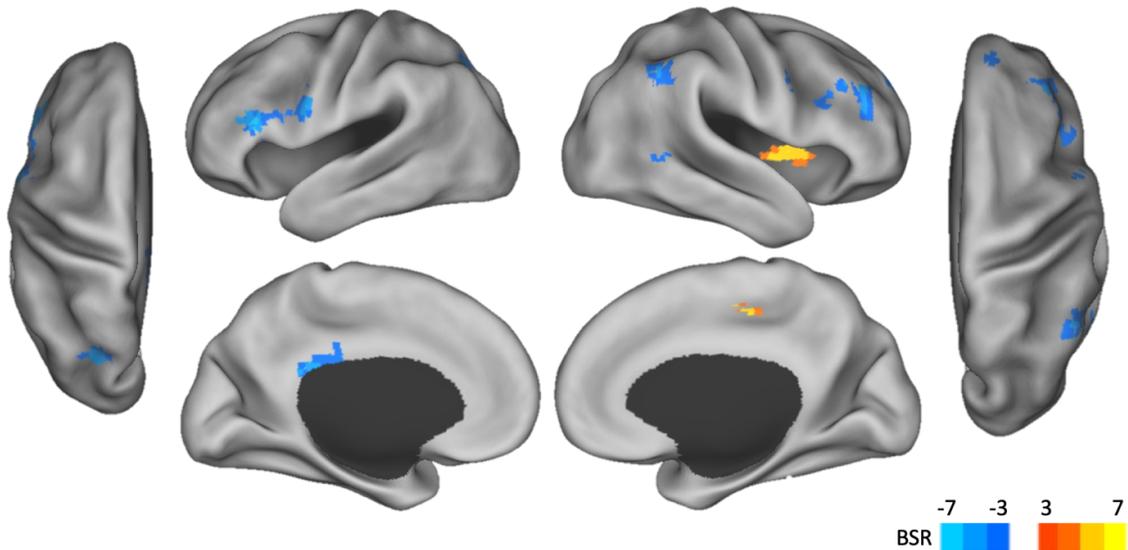
include the right superior and middle frontal gyri, the right IPL, and the right superior temporal gyrus, as well as the left inferior frontal gyrus, the left cuneus, the posterior cingulate cortex (PCC), and the left thalamus. Areas selectively recruited during the final two minutes of the task were the right insula and middle cingulate gyrus. See Table 6 for a list of all coordinates.

### Figure 9

*Brain Scores for each epoch of the TSAT*



*Note.* Brain scores associated with the LV identified by the mean-centred PLS analysis of the TSAT data. Error bars represent 95% confidence intervals determined by bootstrapping analysis.

**Figure 10***Whole-Brain Pattern of Activity Associated with the TSAT*

*Note.* Clusters represent activation associated with the 2<sup>nd</sup> and 4<sup>th</sup> epochs on the TSAT (cool colors) and the final epoch (warm colors). Data are displayed on the left and right hemispheres of a partially inflated surface map. These brain images were generated using a BSR threshold of  $\pm 3.3$  ( $p < .001$ ), minimum cluster size of 20 voxels, and minimum distance between clusters of 10 voxels.

**Table 6***Coordinates associated with Different Epochs of the TSAT*

Brain Region	BA	Cluster Size (in voxels)	MNI Coordinates			BSR
			x	y	z	
<b>Epochs 2 &amp; 4</b>						
Left Inferior Frontal Gyrus	44	241	-51	24	21	6.16
Right Middle Frontal Gyrus	9	163	45	33	33	4.23
Left Posterior Cingulate Gyrus	23	53	0	-39	21	5.79
Left Cuneus	18	47	-12	-98	15	3.50
Left Superior Parietal Lobule	39/7	38	-24	-66	39	3.74
Right Inferior Parietal Lobule	39	37	48	-51	39	3.53
Left Thalamus	50	31	-14	-24	15	5.60
Right Premotor Cortex	6	29	33	-9	27	4.14
Right Superior Frontal Gyrus	9	23	21	51	42	3.85
Right Superior Temporal Gyrus	37	23	63	-54	3	3.31
<b>Epoch 5</b>						
Right Insula	13	50	39	0	12	4.70
Right Middle Cingulate Gyrus	6/31	27	15	-24	45	4.71

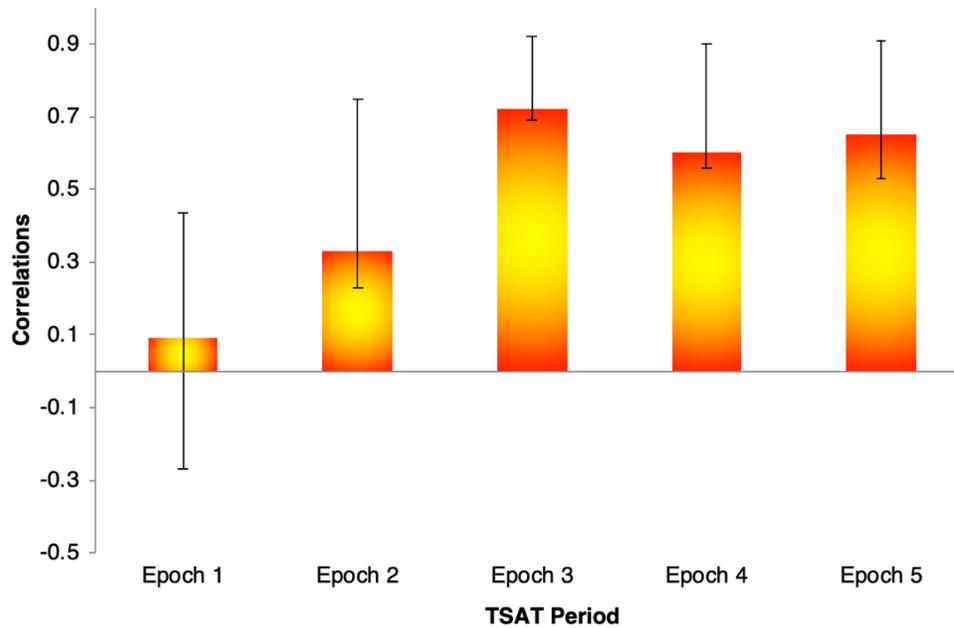
*Note.* Results from the mean-centred PLS analysis of sustained attention. BA = Brodmann Area; BSR = Bootstrap Ratio. Results were thresholded at a BSR of 3.3 ( $p < .001$ ). Minimum cluster size: 20 voxels, minimum distance between clusters: 10 voxels. MNI Coordinates and BSR values are reported for cluster maxima.

**Behavioural PLS analysis.** When we analyzed the TSAT data with participants' vigilance decrement scores, we found one significant LV ( $p < .05$ ), associated with greater vigilance decrement across all but the first epoch. This LV accounted for 29.36% of the overall covariance in the data. See Figure 11 for the correlation values between brain scores and vigilance decrement during each epoch. Figure 12 represents the whole-brain pattern of activation associated with greater vigilance decrement. Individuals with greater vigilance decrement showed greater activation throughout a mostly right-lateralized pattern of brain regions, including the middle and superior frontal gyri, the right ILP, and the right premotor cortex. Along the midline, individuals with higher vigilance decrement recruited

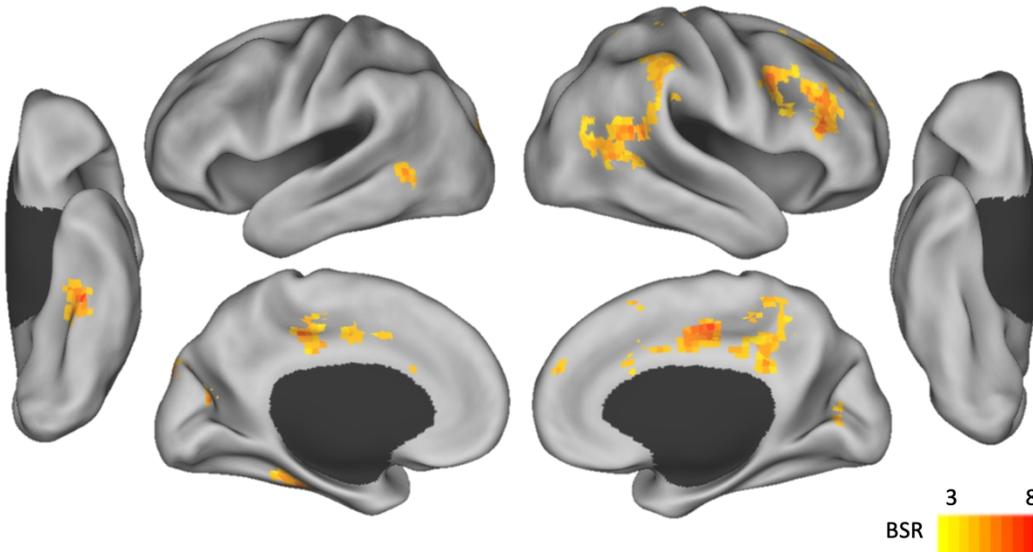
the PCC and cuneus. There was also some left-lateralized activity in the posterior middle temporal and parahippocampal gyri. See Table 7 for coordinates.

### Figure 11

#### *Correlations between Brain Scores and Vigilance Decrement*



*Note.* Correlations are shown for each epoch, as determined by the behavioural PLS analysis of the TSAT. Error bars represent 95% confidence intervals determined by bootstrapping analysis.

**Figure 12***Whole-Brain Pattern of Activity Associated with Greater Vigilance Decrement*

*Note.* Brain areas associated with greater vigilance decrement on the TSAT, across all but the first epoch. Data are displayed on the left and right hemispheres of a partially inflated surface map. Images were generated using a BSR threshold of  $\pm 3.3$  ( $p < .001$ ), minimum cluster size of 20 voxels, and minimum distance between clusters of 10 voxels.

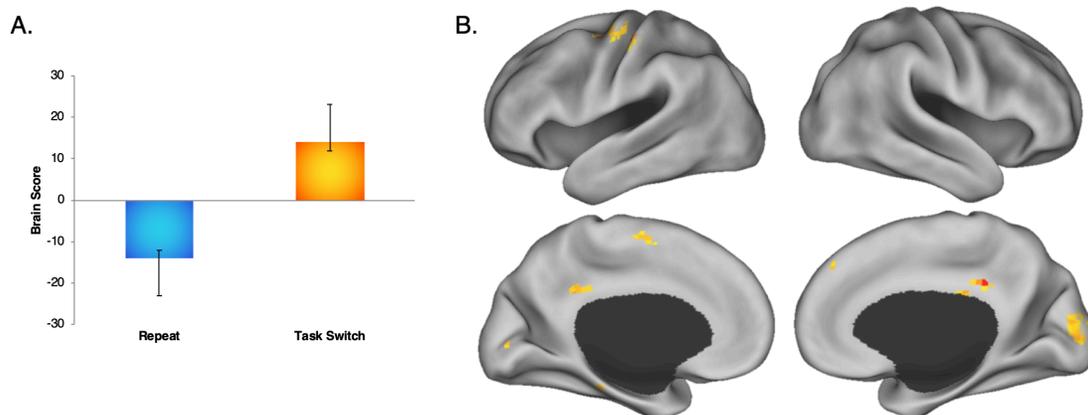
**Table 7***Coordinates associated with Greater Vigilance Decrement during the TSAT*

Brain Region	BA	Cluster Size (in voxels)	MNI Coordinates			BSR
			x	y	z	
Right Middle Frontal Gyrus	9	268	45	27	21	6.52
Left Posterior Cingulate Cortex	23	256	-9	-27	33	6.82
Right Temporoparietal Junction	39	176	54	-45	18	5.56
Right Middle Cingulate Cortex	24	154	12	-18	42	6.96
Right Supramarginal Gyrus	40	92	48	-36	45	5.01
Right Superior Frontal Gyrus	8	84	18	24	48	6.44
Left Cuneus	17	81	-6	-72	12	5.69
Right Premotor Cortex	6	74	42	3	36	5.92
Left Cuneus	18	64	-18	-90	18	5.88
Left Middle Temporal Gyrus	21/37	60	-51	-57	-3	5.35
Left Parahippocampal Gyrus	36	52	-33	-33	-24	7.22

*Note.* Results from the behavioural PLS analysis of sustained attention, using vigilance decrement (median RT during the last epoch vs. median RT during the first epoch) as a behavioural measure. BA = Brodmann Area; BSR = bootstrap ratio. Results were thresholded at a BSR of 3 ( $p < .001$ ). Minimum cluster size: 20 voxels, minimum distance between clusters: 10 voxels. MNI Coordinates and BSR values are reported for cluster maxima.

### **Task switching.**

**Mean-centred analysis.** The basic mean-centred analysis of the NLT data resulted in a significant LV ( $p < .01$ ), dissociating switching from repeat trials. As the experimental model only has two conditions, there was only one source of covariance, and so this LV accounted for 100% of the cross-block covariance. Panel A in Figure 13 represents the brain scores associated with both conditions, and Panel B depicts the pattern of brain activity associated with switch trials specifically. There was limited activity related to switch trials across all time lags. For the second lag (4–6s), brain areas recruited during switching included the left primary sensory & motor cortices, middle and posterior cingulate gyrus, primary visual cortex, and the cerebellum (see Table 8). Coordinates for the activity identified in subsequent lag periods are presented in supplemental materials.

**Figure 13***Brain Scores and Whole-Brain Pattern of Activity Associated with the NLT*

*Note.* A. Brain scores for each condition as determined by the mean-centred PLS analysis of the NLT data. Error bars represent 95% confidence intervals determined by bootstrapping analysis. B. The whole-brain pattern of activity associated with switch trials. Data are displayed on the left and right hemispheres of a partially inflated surface map. Images were generated using a BSR threshold of  $\pm 3.3$  ( $p < .001$ ), minimum cluster size of 20 voxels, and minimum distance between clusters of 10 voxels.

**Table 8***Coordinates associated with Switch Trials during the NLT*

Brain Region	BA	Cluster Size (in voxels)	MNI Coordinates			BSR
			x	y	z	
Left Primary Sensory Cortex	1	90	-48	-21	51	4.04
Left Middle Cingulate Gyrus	23	76	-18	-15	33	5.45
Left Primary Visual Cortex	17	59	-15	-81	12	5.26
Right Primary Visual Cortex	17	59	9	-84	12	3.86
Cerebellum	--	53	3	-87	-24	3.81
Right Posterior Cingulate Cortex	23	36	3	-39	33	4.25

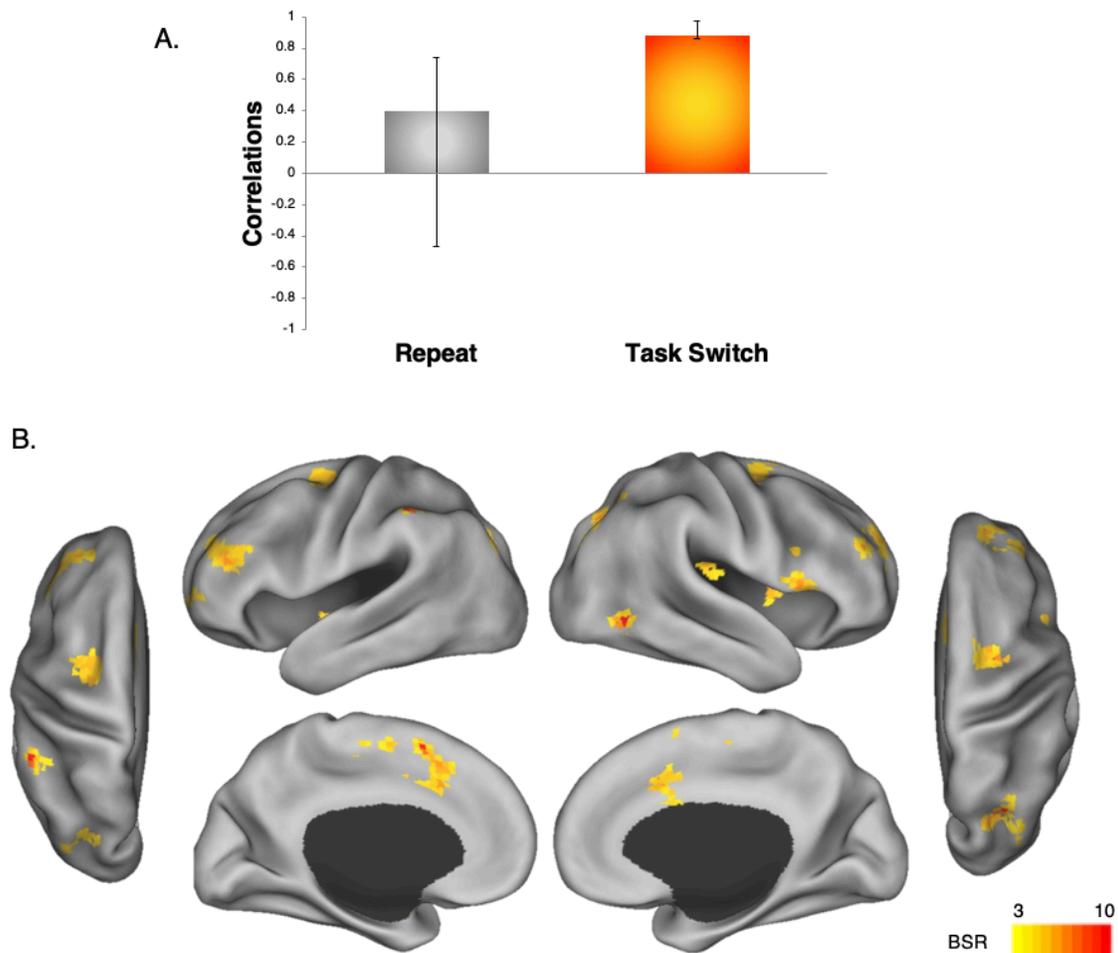
*Note.* Results from the mean-centred PLS analysis of task switching; only switch trial-related activity is reported. BA = Brodmann Area; BSR = Bootstrap Ratio. Results were thresholded at a BSR of 3.3 ( $p < .001$ ). Minimum cluster size: 20 voxels, minimum distance between clusters: 10 voxels. MNI Coordinates and BSR values are reported for cluster maxima.

**Behavioural PLS analysis.** The behavioural PLS analysis of the NLT resulted in a significant LV ( $p < .05$ ) associated with higher switch costs (as measured by the difference in median RT between switch trials and repeat trials.) This LV accounted for 53.55% of the cross-block covariance in the data. The correlation between brain scores and switch cost was significant during switch trials, but not repeat trials (see Figure 14, Panel A). Figure 14, Panel B represents the whole-brain pattern of activation associated with higher switch costs during switch trials (for lag 2). Individuals with higher switch costs recruited regions across both hemispheres in the frontal and parietal lobes, as well as the right temporal lobe. In the frontal lobes, the main areas of activity associated with higher switch costs are the bilateral anterior PFC, left IFG and insula, bilateral superior frontal gyrus, including supplementary motor area (SMA) and pre-SMA on the medial wall, and premotor cortex and frontal eye fields laterally. In the parietal lobes, higher switch costs were associated with bilateral activity in the intraparietal sulcus and left supramarginal gyrus. There was also activity in the lateral fusiform gyrus, on the border between the

temporal and occipital lobes. Higher switch costs were also associated with cerebellar and thalamic activity not represented in Figure 14. See Table 9 for the full list of coordinates.

### Figure 14

#### *Correlations and Whole-Brain Pattern of Activity Associated with Greater Switch Cost*



*Note.* A. Brain scores x switch costs correlations for both types of trials on the NLT. Error bars represent 95% confidence intervals determined by bootstrapping analysis. B. The whole-brain pattern of activity associated with higher switch cost on switch trials. Data are displayed on the left and right hemispheres of a partially inflated surface map. Images were generated using a BSR threshold of  $\pm 3.3$  ( $p < .001$ ), minimum cluster size of 20 voxels, and minimum distance between clusters of 10 voxels.

**Table 9***Coordinates associated with Greater Switch Costs during the NLT*

Brain Region	BA	Cluster Size (in voxels)	MNI Coordinates			BSR
			x	y	z	
Right Cerebellum	--	498	30	-45	-36	7.93
Left Superior Medial PFC	6	293	-12	6	51	9.49
Left Middle Frontal Gyrus	9	196	-36	30	21	6.58
Right Middle Frontal Gyrus	9	140	27	51	33	8.86
Left Cerebellum	--	124	-33	-42	-36	6.22
Right Frontal Operculum	44	123	45	15	12	6.32
Right Posterior IPS	7	121	27	-66	39	7.49
Left Thalamus	50	101	-12	-18	-12	8.15
Right Superior Frontal Gyrus	6	89	21	-6	51	7.69
Right Posterior Insula	13	88	39	-24	21	6.67
Right Lateral Fusiform Gyrus	37	81	45	-60	-6	8.03
Left Posterior IPS	39	61	-27	-66	30	7.51
Left Superior Medial PFC	6	58	-12	-24	51	6.03
Left Supramarginal Gyrus	40	50	-51	-42	48	7.65

*Note.* Results from the behavioural PLS analysis of task switching, using switch costs (median RT for correct switch trials vs. median RT for correct repeat trials) as a behavioural measure. BA = Brodmann Area; BSR = Bootstrap Ratio; PFC = Prefrontal Cortex; IPS = Intraparietal Sulcus. Results were thresholded at a BSR of 3.3 ( $p < .001$ ). Minimum cluster size: 20 voxels, minimum distance between clusters: 10 voxels. MNI Coordinates and BSR values are reported for cluster maxima.

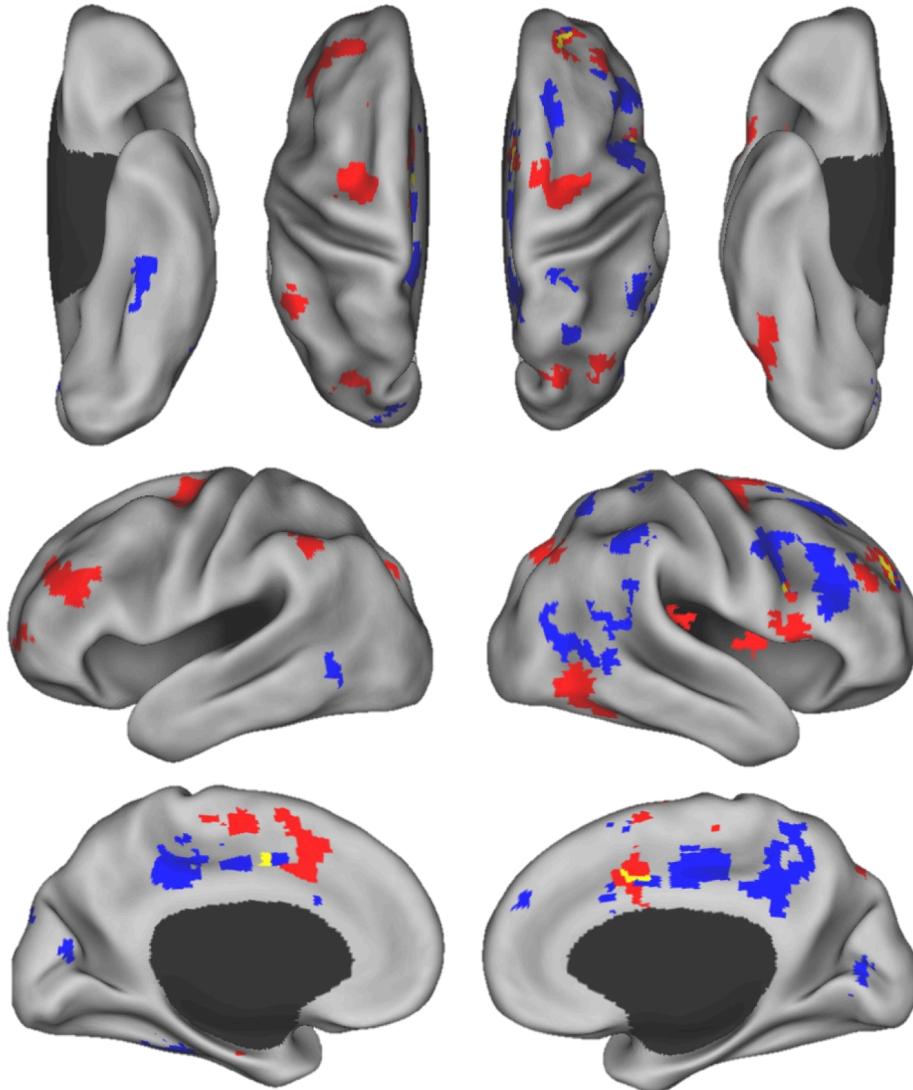
### ***Conjunction Analysis***

We carried out a conjunction analysis of the mean-centred results from the TSAT and NLT. There were no areas of overlap between the switch trial-related activity of the NLT and both of the patterns identified by the TSAT mean-centred analysis (epochs 2 & 4, and epoch 5). We also carried out a conjunction analysis of the behavioural PLS results, to investigate the overlap between performance-driven patterns of activity across tasks. We overlaid the regions of activity correlated to greater vigilance decrement on the TSAT and regions of activity correlated to greater switch cost on the NLT. This analysis revealed minimal areas of overlap (< 40 voxels overall) with no given region of overlap exceeding

10 voxels. Although both behavioural PLS analyses identified frontoparietal patterns of behaviour-related activity, switch cost and vigilance decrement were associated with discrete patterns of activity (see Figure 15).

**Figure 15**

*Conjunction Map of Switch Cost- and Vigilance Decrement-Related Activity*



*Note.* Conjunction map of the behavioural PLS analyses of the TSAT and NLT. Data are displayed on the left and right hemispheres of a partially inflated surface map (left hemisphere images on the left). Blue = areas associated with vigilance decrement; Red = areas associated with switch cost; Yellow = areas of overlap.

## **Discussion**

In the present series of experiments, we investigated the relationship between sustaining and shifting attention. We leveraged both behavioural and neuroimaging methods to examine whether common or distinct neurocognitive control mechanisms govern these two aspects of attention. Overall, our findings provide compelling evidence that the control of attention is regulated by separate systems, dissociable at both the level of the brain and behaviour. We demonstrated that, although task switching and sustained attention are positively correlated, performance on measures assessing these abilities is best represented by a dual-factor model, implying a distinct pattern of performance across both sets of tasks. This confirmed our first hypothesis that behavioural performance on tasks of vigilance and shifting would be dissociable. We then extended these findings to brain function, where performance on matched switching and vigilance tasks was associated with non-overlapping patterns of neural activity across known regions of cognitive control. This provided support for our second hypothesis that vigilance and shifting rely on distinct brain areas. Taken together, these studies show that, while these two processes may not be in direct competition, they represent discrete cognitive abilities mediated by separate control mechanisms in the human brain.

### **Factor Analysis Findings**

We used factor analysis to evaluate the patterns of performance in a large cohort of participants across a variety of switching and vigilance tasks. As CFA requires a priori hypotheses regarding the relationships between observable variables and latent factors, it allowed us to test three possible models of attentional control directly. The existing literature provided theoretical and empirical support for both single-factor and dual-factor

models. Unitary views of cognitive control, such as the Large-Scale Distributed Network (Mesulam 1981, 1990, 1999), the Supervisory Attentional System (Norman & Shallice 1986; Stuss et al., 1995), the Guided Activation Theory (Miller & Cohen, 2001), the Multiple Demand System (Duncan et al., 2010), or the Superordinate Control Network (Niendam et al., 2012), all describe a solitary top-down mechanism directing the focus of attention. In the case of the single executive system, we might expect that performance across all tasks would closely covary. In a test of this hypothesis, we found that a sole factor representing the executive control of attention provided adequate fit of the observed pattern of performance across tasks. However, this model did not fit the data as well as the two-factor alternative.

The two-factor model posits that different aspects of attention rely on different cognitive mechanisms. Theories consistent with this model include the three-network model (Posner & Petersen, 1990; Petersen & Posner, 2012) and the top-down vs. bottom-up model (Corbetta & Shulman, 2002). These frameworks propose that the sustaining and shifting of attention are discrete cognitive constructs (with distinct neuroanatomical correlates). They would therefore predict that performance on task switching and sustained attention tasks should dissociate, loading onto separate factors. In our modeling, the factors representing sustained attention and task switching were free to covary with each other, allowing for the possibility that the two processes are separate but related. Ultimately, this model outperformed the others on all measures of model fit, offering strong evidence that this two-factor model best represented the observed variance in the data. While the strength of the relationship ( $r = .57$ ) did not negate discriminant validity, performance across tasks was not wholly independent.

The two-factor model identified a positive correlation between the sustained attention and task switching factors. It is possible that we could have found a negative relationship between these two factors. There is a natural tension between the ability to maintain focus without succumbing to distraction, and the ability to quickly and accurately react to external cues that require us to flexibly switch our behaviour (Gruber & Goschke, 2004). As such, aptitude in one ability might require the active suppression of the other. Some research on multitasking provides indirect support for this hypothesis, showing that those who multitask often may be worse at maintaining focus over time (e.g., Ralph et al., 2015; Uncapher & Wagner, 2018). Had it been the case that shifting and vigilance were competing processes, we might have discovered a negative correlation between the two factors. This is not what we found.

We also tested a third hypothesis, where the two latent factors did not covary. This analysis allowed us to examine the possibility that the two processes are wholly independent. By modeling orthogonal factors, we were able to investigate whether the ability to sustain attention is neither positively or negatively correlated with the ability to switch efficiently. Our findings show that, at least in this neurologically healthy sample of young adults, this was not the case. In fact, this model had the weakest model fit statistics of the models we tested. Taken together, these results do not support the hypothesis that these processes compete with each other or that they are entirely independent from each other. This is consistent with the established understanding that most cognitive abilities are positively correlated, as shown by multiple CFA investigations of cognitive functioning (e.g., Carroll, 1993; Keith & Reynold, 2018; Miyake et al., 2000; Taub & McGrew, 2004;

Tucker-Drob & Salthouse, 2009), and dating all the way back to Charles Spearman's work at the turn on the 20<sup>th</sup> century (Spearman, 1904).

### **Neuroimaging Findings**

We designed the neuroimaging experiment to identify the brain regions supporting sustained attention and task switching across the brain. We were confident in the construct validity of the two tasks used in this study, as they showed the largest factor loadings on their respective constructs in the factor analysis. In contrast to the CFA study above, where we defined *a priori* hypotheses according to specific models of attentional control, here we adopted a data-driven approach in analyzing the neuroimaging data. Although our analysis of the behavioural data revealed dissociable patterns of performance, it was still possible that both tasks relied on similar networks at the level of the brain. We, therefore, selected a method of analysis that would allow the patterns present in the data to emerge without imposing *a priori* contrasts. The two tasks were also analyzed separately, which allowed patterns of brain activity associated with each task to emerge independently, rather than selectively identifying patterns of brain activity that dissociated the two processes.

#### ***Sustained Attention***

In our primary “mean-centred” analysis of sustained attention, we found two patterns of brain activity. The first pattern of activity emerged during the middle period of the task (from the 2-minute to 8-minutes mark). It was composed of a right-lateralized thalamo-fronto-parietal series of regions, compatible with the established sustained attention network. This network was initially defined over two decades ago (e.g., Coull et al., 1996, 1998; Lewin et al., 1996; Pardo et al., 1991; Paus et al., 1997; Sturm, 1999) and corroborated by more recent studies (e.g., Langner & Eickhoff, 2013; O'Connor et al.,

2011). The regions identified in this analysis also overlap with the FPCN (in the right hemisphere), as defined by several studies of intrinsic functional connectivity (e.g., Power et al., 2011; Spreng et al., 2013; Vincent et al., 2008). The recruitment of the FPCN likely reflects active task engagement throughout the majority of the 10-minute task. We also found activity in the posterior cingulate gyrus, an area more commonly associated with the default mode network (DMN) (Raichle, 2015; Raichle et al., 2001). Activity in this region is not entirely unexpected: the TSAT is a simple, lengthy, and monotonous task. It is thus likely that there was some amount of mind wandering taking place. This is particularly true midway through the 10-minute task when the task-set has already been established, but fatigue (and the accompanying requirement for additional focus to fight vigilance decrement) has not yet set in. Several recent studies of sustained attention have demonstrated that fluctuations in behavioural measures of performance during a vigilance task correlate with activity in the DMN in addition to known attentional networks (e.g., Esterman et al., 2013, 2014; Fortenbaugh et al., 2018; Rothlein et al., 2018). These findings establish that tasks of sustained attention often elicit activity in both the control and default networks of the brain (Fox et al., 2005), as seen in the first of two patterns identified in our data.

The other pattern of brain activity identified by our data-driven analysis emerged in the final two minutes of the task. This period was associated with the selective recruitment of the right insular cortex and a small cluster of activity in the middle cingulate cortex. The dissociation of neural activity at this point in the task is of interest, as this period corresponds to the time during which vigilance decrement typically begins to be observable (Ballard, 1996). The activity we identified during this epoch (see Figure 10)

maps onto two critical nodes of the cingulo-opercular network (Dosenbach et al., 2006, 2007, 2008), reportedly responsible for the stable maintenance of task-set. It is possible that, as maintaining focus on the task becomes particularly taxing, there is an amplified reliance on this maintenance network to remain on-task.

However, there is an alternate view of cingulo-opercular functioning. Seeley and his coauthors argue that the anterior insular and ACC make up the “salience network,” which responds to relevant and meaningful stimuli (Seeley et al., 2007). In their model of attentional control, Corbetta and Shulman also describe the role of the insula in stimulus-driven control (Corbetta & Shulman, 2002; Corbetta et al., 2008). Additionally, Menon and Uddin argue that the insula facilitates attentional control by regulating the activation of different networks in response to salient events (Menon & Uddin, 2010). In this alternate view of insular function, this region acts as a circuit breaker, tripped by relevant exogenous stimuli. The role of the insula is therefore transient and tied explicitly to discrete salient events (and thus incompatible with the dual-network view proposed by Dosenbach and colleagues). When considered through this lens, it is possible that the increased activity we detected in the right insula and cingulate cortex in the later stages of the sustained attention task represents a transient enhancement of stimuli salience rather than static maintenance of task set. Whatever the case may be, it appears as though this set of regions is critical in supporting the continued maintenance of attention as vigilance begins to wane.

In addition to the analysis described above, we also investigated the effect of behavioural performance on brain activity by including measures of performance in our analysis. Here, we found a significant pattern of brain activity associated with vigilance decrement: a clear pattern of right-lateralized frontoparietal activity, with smaller clusters

of activity in the left temporal lobe. There was no pattern of brain activity correlated with better performance (i.e., smaller vigilance decrements). While we might expect better performance to be associated with activity in cognitive control regions, existing studies of sustained attention show that the opposite may be the case. In a study comparing two versions of the SART, activity in the right dlPFC was greater under “low-challenge” conditions, where both healthy participants and brain-injured patients performed more poorly (Manly et al., 2003). Moreover, Esterman and colleagues found that periods of variable task performance were related to increased activity in task-positive network regions, putatively due to more effortful processing (being “out of the zone”). This was in contrast to “in the zone” periods, which the authors described as phases of “effortless” processing, characterized by more stable and accurate task performance and a relative increase in DMN activity (Esterman et al., 2013). Fortenbaugh and her coauthors later replicated these findings (Fortenbaugh et al., 2018). They demonstrated that activity in task-positive regions (specifically in the dorsal and ventral attention networks) coincided with periods of variability in task performance. Taken together, these previous reports and our current results suggest that vigilance decrement may be related to heightened engagement of endogenous and exogenous attention systems, as individuals struggle to maintain focus.

### ***Task Switching***

Our primary “mean-centred” analysis of the task switching data revealed very few regions of switch-related activity. In designing our switching task, we added static task cues to the display to minimize working memory load associated with keeping the task-location mapping in mind. Reducing the memory load was meant to isolate activity related

exclusively to switching processes. However, it is possible that this manipulation reduced the differences between repeat and switch trial-related activity to levels undetectable by the current study design. Previous reviews of the neural underpinnings of task switching note that there are no brain structures exclusively recruited by task switching. Regions that support task switching are also recruited by working memory demands (Wager et al., 2004) and often by matched control tasks (Ruge et al., 2013). Similarly, previous work by our research group has suggested that working memory may represent a common feature of executive control (Lemire-Rodger et al., 2019). It is, therefore, possible that diminishing working memory demands may reduce overall activity in “task-positive” networks.

The repeat and switch trials were identical in every respect – the only difference between them was the continuation or alteration of the rule set from the previous trial. Switches happened predictably, and the task-cue was present at all times. These parameters made the task particularly simple in terms of task switching paradigms (Kiesel et al., 2010; Monsell, 2003). Despite the simple task design and the limited amount of switch-related activity identified in our analysis, we still found a significant effect of switching in terms of both reaction time and accuracy. This finding is consistent with the literature that shows that switch costs persist even when switches are predictable (e.g., Dreher et al., 2002; Monsell et al., 2003; Tornay & Milán, 2001), or when there is a long preparatory period (e.g., Altman, 2002; Jost et al., 2013; Ruge et al., 2013; Schmitz & Voss, 2014). As our analysis was entirely data-driven, and with all other cognitive demands being equal across trials, it is possible that the most salient difference in BOLD signal between the two conditions was the slightly delayed motor response on switch trials. This may account for the switch trial-related activity identified in primary sensory-motor areas. Shifts in attention

can occur very quickly, making them difficult to capture with fMRI methods (Posner, 2014). Combined magnetoencephalography and fMRI methods have much higher temporal resolution and so may be better suited to detecting shift-related activity in straightforward designs as was implemented here (Dale et al., 2000).

When we included measures of task switching performance in the analysis, we identified a pattern of switch-related activity that was much more in line with conventional fMRI studies of task switching (for meta-analyses, see: Buchsbaum et al., 2005; Kim et al., 2012; Wager et al., 2004). Similar to our sustained attention results, we found a widespread pattern of mostly frontoparietal activity correlated with poorer performance (increased switch cost). Much like vigilance, switching tasks are also characterized by periods of variability, necessitating increased cognitive control as performance wavers. Higher switch costs correlated with increased activity bilaterally, notably in the frontal eye fields (FEF) and intraparietal sulci (IPS). These are primary nodes of the Dorsal Attention Network (DAN), responsible for the top-down control of attention (Corbetta & Shulman, 2002; Corbetta et al., 2008). We also find left-lateralized activity in the IPL, a region reliably identified in the literature on task switching (e.g., Braver et al., 2003; Dove et al., 2000; Dreher et al., 2002; Kimberg et al., 2000; Lemire-Rodger et al., 2019; Ravizza & Carter, 2008; Ruge et al., 2005; etc.). Research has also shown that IPL activation correlates with poor performance on measures of task switching (Connell et al., in prep; Ravizza & Carter, 2008). Our results revealed performance-related activity in the right IFG and insula as well, lending support to Menon and Uddin's theory of the insula as a hub for switching (Menon & Uddin, 2010). Finally, we identified a large cluster of activity in the right cerebellum. Though authors tend to focus on cortical activity associated with

cognitive tasks, cerebellar activity, particularly on the right, is commonly observed in shifting tasks and is thought to play a critical role in stimulus-response mapping (Bischoff-Grethe et al., 2002; Desmond et al., 1998; Dreher et al., 2002; Wu et al., 2013).

### **Separate Mechanisms of Attentional Control**

The most striking feature of our conjunction analysis was the almost complete lack of overlap between the regions identified in our analyses of task switching and sustained attention (Figure 15). Although both processes are known to recruit frontoparietal areas, it appears that the specific structures most reliably recruited by each task are different. This lack of overlap is particularly remarkable as we designed the neuroimaging experiment to maximize the probability of finding similar patterns of activity across the two tasks. We carefully matched the tasks in terms of design and cognitive demands, we used an analysis that did not depend on pre-defined contrasts, and we employed a repeated-measures design. Nonetheless, as participants perform these tasks, they engage distinct sets of areas to maintain their performance.

Our results provide clear support for the fractionation of attentional control in the human brain. Unitary models of attention cannot adequately account for the disparity between the two patterns of activity identified in our current work. We must, therefore, consider non-unitary accounts. We reviewed all the areas identified in our analysis against existing models of attention and cognitive control that make different predictions about the neuroanatomical correlates of various aspects of attention. We carried out a region-by-region comparison of our results against Corbetta and Shulman's endogenous vs. exogenous model (Corbetta & Shulman, 2002; Corbetta et al., 2008), Dosenbach and colleagues' dual-network model of adaptive control and set-maintenance (Dosenbach et

al., 2006, 2007, 2008), and finally Yeo and colleagues' 7-network parcellation of the brain, based on intrinsic functional connectivity (Yeo et al., 2011). Though our results did not overlap perfectly with any of the models considered, our data best mapped onto the Corbetta and Shulman model (Corbetta et al., 2008). Four of the five nodes of the DAN described by these authors corresponded with areas we identified in our behavioural analysis of task switching (the left FEF, bilateral IPS, and right "visual areas" at the junction of the temporal and occipital lobes). Half of the regions belonging to the putative Ventral Attention Network (VAN) overlapped with our sustained attention findings (the right MFG and the right temporoparietal junction). This supports, at least in part, Corbetta and Shulman's hypothesis posited in their original paper (2002) that the shifting of task set relies on top-down attentional control via the DAN, while the VAN is critical for vigilant attention.

While these findings offer a coherent view of attentional control, they were also somewhat unexpected. In line with Corbetta and colleagues' 2008 review, we expected that maintaining focus in the face of fatigue would rely on the top-down control via the DAN, while switching, which relies on exogenous stimuli, would selectively recruit the VAN. Instead, our findings suggest that, as participants' performance dips, tasks of vigilance require enhanced stimuli-related processing, and switching tasks require enhanced goal-directed processing. Though initially unanticipated, the conclusion that sustained attention relies on bottom-up processing is compatible with previous literature (e.g., Corbetta & Shulman, 2002; Coull et al., 1998; Manohar et al., 2014). Research shows that the addition of an exogenous cue can improve performance on vigilance tasks, in line with a stimulus-driven account of sustained attention (Manly et al., 2002; O'Connor et al., 2004). We also

find that the IFG and insula dissociated from the rest of the VAN, as right opercular/insular activity was associated with higher switch costs and not vigilance decrement. Enhanced recruitment of the right IFG was likely due to the greater need for response inhibition in the switching condition (Aron, Robbins, & Poldrack, 2004). Meanwhile, insular activity suggests enhanced salience of stimuli and switching between networks (Menon & Uddin, 2010; Seeley et al., 2007) as switch costs increase.

Our results were also unexpected in that they did not replicate Dosenbach and colleagues' dual-network model (2006, 2007, 2008). In our analysis, regions identified by these authors as related to sustained set maintenance (i.e., insula, aPFC, and ACC) were correlated with performance on task switching and not sustained attention. As for regions they consider to be responsible for trial-wise "adaptive control," (i.e., the dlPFC and IPL), we found an effect of task on laterality. In the dlPFC and IPL, higher switch costs were associated with left-lateralized activity, while greater vigilance decrement was associated with right-lateralized activity. This pattern of laterality is compatible with an updated version of the SAS model (Shallice, 2004; Shallice, Stuss, Picton, et al., 2008a; Stuss, 2011). In this revised framework, they abandon the concept of a central executive and focus instead on the specialized functions within the structures of the frontal lobes. The dlPFC is responsible for task setting on the left, and ongoing monitoring on the right. Our findings suggest that this lateralized pattern of specialized function extends to the IPL as well.

### **Clinical Implications**

The study of attention is intrinsically rooted in patient work. Brain lesion research over the last century has allowed us to establish the neuroanatomical basis of different attentional processes. The study of neglect initially led to the development of right-

lateralized theories of attention (e.g., Heilman & van den Abell, 1980; Mesulam, 1981). Early work with frontal lesion patients identified that they struggled with flexible and adaptive behaviour (e.g., Milner, 1963; Stuss & Benson, 1984). Our present research is one of many extensions of this canon, using functional neuroimaging to investigate these questions in healthy young adults to offer novel contributions to our understanding of attention. We present the first direct investigation of both the sustaining and shifting of task-set within the same participant group, thus laying the groundwork for future research into the disruption of these two systems in clinical populations. We confirm that, despite the increased prominence of a core FPCN in the literature, not all goal-directed cognition relies on the same brain regions. Our findings consequently underscore the importance of assessing different attentional abilities independently from one another in the context of clinical neuropsychological assessment. Vigilance and cognitive flexibility should also constitute separate targets for cognitive rehabilitation and attention training, as we cannot assume transferability between these abilities.

Our work also proposes a new measure of sustained attention with promising potential for use in clinical settings: the TSAT. It is well-established that sustained attention is vulnerable to brain injury (Parasuraman et al., 1991; Shallice, Stuss, Alexander, et al., 2008; Stuss et al., 1989), but many standard measures of sustained attention have additional cognitive requirements (Grahn & Manly, 2012; Robertson et al., 1997). Robertson and colleagues first developed the SART to address some of these limitations (Robertson et al., 1997). The TSAT shares many of the advantages of the SART as a measure of sustained attention while avoiding the potential response inhibition issues inherent in the design. Like the CCPT, the TSAT requires the binding of two aspects of the presented stimulus to detect

a target, precluding any pre-attentional processing of target stimuli. However, unlike the CCPT, the TSAT does not show a meaningful ceiling effect. Moreover, given that the TSAT requires a response on every trial, the TSAT produces reaction time data for both targets and non-target, which allows for a detailed analysis of performance. The TSAT also has minimal processing speed, working memory, and language requirements, limiting cofounds from other cognitive domains. Finally, the TSAT had the highest factor loading of all tasks studied on a factor representing sustained attention, which speaks to the task's robust construct validity. Future research is needed to determine the specificity and reliability of this new measure, but with proper validation, the TSAT may become a useful clinical assessment tool.

### **Limitations & Future Directions**

The present work represents an in-depth examination of the relationship between the sustaining and shifting of attention. Notwithstanding, the generalizability of our findings is limited as we only investigated attention in a young, healthy sample of undergraduate students. Understanding the dynamics between these two processes in other groups, such as healthy and pathological aging, acquired brain injury, and neuropsychiatric disorders, remains the subject of future studies. Current research in the field has also emphasized performance variability, rather than vigilance decrement, as the critical measure of sustained attention (e.g., Esterman et al., 2013, 2014; Esterman & Rothlein, 2019; Fortenbaugh et al., 2018; Rothlein et al., 2018). Although we did examine measures of performance variability in our preliminary analyses, ultimately, we focused on overall error rate data in our CFA study, as this measure showed the strongest correlations between tasks. Since participants were asked to complete multiple cognitive tests and questionnaires

in a single session, the duration of the individual sustained attention tasks in our behavioural study were modest — this curtailed observable vigilance decrement. Nonetheless, the use of overall error rate was consistent with the research literature (e.g., Robertson et al., 1997; Shalev et al., 2011) and clinical measures of sustained attention (Epstein et al., 1998; Robertson et al., 1996; Ruff et al., 1992). Still, it would be worthwhile to replicate the current findings using lengthier tasks to capture both vigilance decrement and variability.

We examined the relationship between maintaining focus on one task and the deliberate shifting of attention to another task. However, if we were to construct a more ecologically valid model of attentional control, we would want to include both voluntary and involuntary shifts of attention. Future work will explore distractibility and its effects on both vigilance and cognitive flexibility. Some of this research will center on the modulating impact of frequent digital multitasking on cognition and brain activity. Though the evidence is currently mixed, early research in this field suggests that this type of multitasking may correlate with more frequent attentional lapses (Uncapher & Wagner, 2018). Moreover, preliminary fMRI results show that higher levels of self-reported social media use modulate neural recruitment during a vigilance task (Lemire-Rodger et al., 2018). A cross-sectional investigation of attention and multitasking across generations would also be valuable in furthering our understanding of the effects of technology and aging on our ability to maintain focus.

## **Conclusion**

We provide compelling evidence for the dissociation of sustained attention and task switching, both at the behavioural and neural levels. Our findings show that performance

across a variety of attentional tasks was best explained by two separate but related factors representing shifting and sustained attention. These two factors were also distinct in terms of neural activity, with behavioural performance on each type of task correlating with non-overlapping patterns of activity across the brain. Overall, this is consistent with a fractionated account of attentional control. In particular, we corroborate the exogenous vs. endogenous view of attention (Corbetta & Shulman, 2002), as greater switch costs drove the recruitment of the DAN while larger vigilance decrements drove the recruitment of the VAN. This work offers a clear impression of the dual nature of sustaining and shifting attention in the human brain and deepens our understanding of the neurocognitive mechanisms underlying conscious awareness.

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## Appendix A: Supplementary Materials

### Supplementary Tables for the Confirmatory Factor Analysis

**Table I**

*Pearson Correlation Coefficients between Tasks - Error Rate Data*

Task	CCPT	SART	TSAT	LGT	NLT	VDT
CCPT	--					
SART	.19*	--				
TSAT	.23**	.48**	--			
LGT	.08	.15*	.18*	--		
NLT	.08	.19*	.26**	.20*	--	
VDT	.08	.11	.18*	.18*	.24**	--

*Note.* Correlations between overall error rate (for sustained attention tasks) and error rate switch costs (for task switching tasks). \*  $p < .05$ , \*\*  $p < .001$

**Table II**

*Pearson Correlation Coefficients between Tasks - Median RT Data*

Task	CCPT	SART	TSAT	LGT	NLT	VDT
CCPT	--					
SART <sup>♦</sup>	.08	--				
TSAT	.18*	.01	--			
LGT	.05	.11	.07	--		
NLT	.11	-.09	-.03	.08	--	
VDT	-.08	.12	.08	.08	.12	--

*Note.* Correlations between median RT change for sustained attention tasks (4<sup>th</sup> quartile median RT vs. 1<sup>st</sup> quartile median RT) and median RT switch costs for task switching tasks (median RT on repeat trial vs. median RT on switch trials). <sup>♦</sup>No median RT data is available for target trials on SART, so overall error rate is used in these correlations. \*  $p < .05$

**Table III**

*Fit Indices for CFA Models Calculated using Transformed Error Rate Data for Sustained Attention Tasks*

Model	$\chi^2$	df	Fit Indices				
			CFI	TLI	AIC	RMSEA	SRMR
One-factor	16.71	9	.93	.88	6557.00	.06	.05
Two-factor	2.34	8	1.00	1.10	6545.16	.00	.02

*Note.* CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; AIC = Akaike's Information Criterion; SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation.

### **Additional Coordinate tables for Mean-Centred Analysis of Task Switching**

**Table IV**

*Coordinates associated with Switch Trials during the Number Letter Task – Lag 3*

Brain Region	BA	Cluster Size (in voxels)	MNI Coordinates			BSR
			x	y	z	
Left Premotor Gyrus	6	20	-33	-6	30	5.05
Left Amygdala	53	61	-21	-3	-18	3.81
Left Middle Occipital Gyrus	19	23	-51	-69	0	3.67

*Note.* Results from the mean-centred PLS analysis of task switching, Lag 3. BA = Brodmann Area; BSR = bootstrap ratio. Results were thresholded at a BSR of 3.3 ( $p < .001$ ). Minimum cluster size: 20 voxels, minimum distance between clusters: 10 voxels. MNI Coordinates and BSR values are reported for cluster maxima.

**Table V**

*Coordinates associated with Switch Trials during the Number Letter Task – Lag 4*

Brain Region	BA	Cluster Size (in voxels)	MNI Coordinates			BSR
			x	y	z	
Left Fusiform Gyrus	37	55	-24	-33	-18	5.40
Left Supramarginal Gyrus	40	59	-27	-39	18	4.35

*Note.* Results from the mean-centred PLS analysis of task switching, Lag 4. BA = Brodmann Area; BSR = bootstrap ratio. Results were thresholded at a BSR of 3.3 ( $p < .001$ ). Minimum cluster size: 20 voxels, minimum distance between clusters: 10 voxels. MNI Coordinates and BSR values are reported for cluster maxima.

**Table VI***Coordinates associated with Switch Trials during the Number Letter Task – Lag 5*

Brain Region	BA	Cluster Size (in voxels)	MNI Coordinates			BSR
			x	y	z	
Left Cerebellum	--	108	-6	-42	-39	4.47
Left Fusiform	37	24	-39	-42	-6	4.44

*Note.* Results from the mean-centred PLS analysis of task switching, Lag 5. BA = Brodmann Area; BSR = bootstrap ratio. Results were thresholded at a BSR of 3.3 ( $p < .001$ ). Minimum cluster size: 20 voxels, minimum distance between clusters: 10 voxels. MNI Coordinates and BSR values are reported for cluster maxima.