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An fNIRS investigation into the development of executive function across the school transition period

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PREFACE

The data presented in this thesis were collected by the PhD candidate with the assistance of several undergraduate students, who were trained and supervised by the candidate. Each manuscript contained in the thesis was drafted by the PhD candidate and is their own work. The manuscripts were revised and edited by Dr. Eva Rafetseder, Dr. Sobanawartiny Wijeakumar, and Dr. Yee Lee Shing. All co-authors have agreed for the manuscripts to be used in this thesis. This project received full ethical approval from the General University Ethics Panel at the University of Stirling.

ABSTRACT

Between the ages of four- to six-years-old, children show remarkable improvements in executive functioning (EF). This thesis aimed to determine which factors contribute to the neurocognitive development of two types of EF, namely, visual working memory (VWM) and inhibitory control (IC). Home-based longitudinal assessments of behaviour, brain function (using functional near-infrared spectroscopy – fNIRS), and academic success were collected across two consecutive years. Chapters 2 and 4 examined which key factors contribute to individual differences in pre-schoolers' VWM and IC and their neural correlates. Children were categorised into high-performing (HP) and low-performing (LP) groups based on their performance. Chapter 2 found that LPs compared to HPs, increasingly activated the left frontal and bilateral parietal cortices when their VWM capacity was challenged. Further, activation in the left parietal cortex partially mediated the association between parent-reported stressful life events and VWM performance. Chapter 4 found that LPs increasingly activated the bilateral frontal and parietal cortices when their inhibitory processes were strained. Chapters 3 and 5 examined the longitudinal development of VWM and IC and their neural correlates, and how the developmental trajectories of these functions differ by the schooling experience. Further, the extent to which schooling-related changes in EF could predict academic outcomes over time was investigated. Chapter 3 found that children who attended one year of schooling (P1) improved more in VWM than children who stayed in kindergarten (KG). Additionally, P1 children who began the year with greater VWM skills gained more in vocabulary across the school year. Chapter 5 found that P1 children, compared to KG children, showed a greater change over time in activation related to more efficient response monitoring in the bilateral frontal cortex. Further, the change in the left frontal activation difference showed a positive trend with mathematical ability. The novel research presented in this thesis broadens our understanding of individual differences in EF and underlying brain function. Further, these findings reveal how the schooling environment shapes the neurocognitive development of EF which has important implications for academic success.

ACKNOWLEDGMENTS

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

A'	Accuracy
ACC	Anterior cingulate cortex
ADHD	Attention deficit hyperactivity disorder
CDT	Cats-and-Dogs Task
dlPFC	Dorsolateral pre-frontal cortex
EEG	Electroencephalogram
EF	Executive function
ERN	Error-related negativity
ERP	Event-related potential
ERP	Error-related positivity
FA	False alarms
fMRI	Functional magnetic resonance imaging
fNIRS	Functional near-infrared spectroscopy
H	Hits
HbO	Oxygenated haemoglobin
HbR	De-oxygenated haemoglobin
HOME	Home Observation for Measurement of the Environment
HP	High-performers
IC	Inhibitory control
K	Capacity
KG	Kindergartners
LCS	Latent change score
LP	Low-performers
LPFC	Lateral pre-frontal cortex
P1	Primary 1
PFC	Pre-frontal cortex
PPC	Posterior parietal cortex
ROI	Regions of interest
SEM	Structural equation modelling
SES	Socio-economic status
T1	Timepoint 1
T2	Timepoint 2
VWM	Visual working memory
WM	Working memory

CHAPTER 1 EXECUTIVE FUNCTION DEVELOPMENT IN CHILDHOOD: A
REVIEW OF THE LITERATURE

1.1 Introduction

This thesis investigates how individual differences and environmental factors contribute to the development of executive function (EF) and its neural correlates between the ages of four- to six-years-old. Although many definitions of EF exist, some broader than others, researchers agree it is a term used to describe a set of neurocognitive processes involved in goal-directed behaviour. These set of skills are not just important, but they are necessary for sustaining mental and physical health and for supporting cognitive, social, and psychological development (Diamond, 2013). Specifically, EF is associated with school readiness (Müller et al., 2008), academic achievement (Alloway & Alloway, 2010; Blair & Razza, 2007; Bull & Scerif, 2001; Duckworth et al., 2019; Gathercole, Pickering, Knight, et al., 2004; Gawrilow et al., 2014; McClelland et al., 2014) and predicts long-term developmental outcomes into adulthood such as health, wealth, and criminal activity (Moffitt et al., 2011). Critically, between the ages of four- to six-years-old, children begin to show remarkable improvements in EF (for a review see Garon et al. 2008). These improvements are proposed to result from a combination of factors, including individual characteristics of the child as well as concurrent changes in their environment (Sameroff & Haith, 1996). Importantly, this developmental period coincides with the start of formal school education, where children are required to follow rules in a structured environment, drawing heavily on their EF processes. Thus, this raises the question of whether the schooling environment itself might foster EF development.

This PhD thesis will attempt to better understand the factors which contribute to the development of EF in young children by initiating a research program that combines an experimental approach with longitudinal assessments of brain functions (measured using functional near-infrared spectroscopy – fNIRS), cognitive abilities, and academic performance. The data presented in this thesis were collected on children in their homes in Scotland

across two consecutive years (2018 – 2019). To isolate the unique contributions of schooling on EF development, this thesis employed a modified school cut-off design. In Scotland, school commencement dates fall in August each year, with the school starting year cohort consisting of children born between the beginning of March in one year (aged 5.5) and the end of February (aged 4.5) of the following year. However, parents of children born in January and February each year can choose to enrol their child into school or defer their entry until the following year, and these requests are automatically approved. This results in two groups of children who are close in age but who differ in their experience in a school context.

The aim of this chapter is to provide a review of the developmental literature on EF, with particular emphasis on working memory (WM) and inhibitory control (IC). The most prominent theoretical accounts of each construct and how they might develop are discussed. Some of the common methods for measuring WM and IC are presented followed by a review of the neurodevelopmental literature. Several factors are outlined for their role in contributing to the individual differences in WM and IC development. Finally, the main research questions of the thesis are presented alongside an outline of each chapter.

1.2 Defining executive function

EF (also referred to as executive / cognitive control) is an umbrella term used to describe a set of top-down cognitive processes involved in controlling goal-directed behaviour and is primarily associated with an increase in activity in the pre-frontal cortex (PFC) (Diamond, 2013; Goldstein et al., 2014). Before the advent of modern-day neuroimaging techniques, the concept of a central control mechanism located in the PFC was discussed as far back as the mid-1800s, when Phineas Gage suffered an accident that resulted in a large metal rod piercing through his frontal lobe. Although he survived, his left frontal lobe was severely damaged leading to profound personality and behavioural changes. Most notably, Phineas was described as having become impatient,

unstable, and capricious following the accident (Harlow, 1993). Thus, early neuroscientists began researching the potential of the frontal lobe for housing a central executive mechanism responsible for effortful, goal-directed behaviours. Neuropsychologist Luria was perhaps the first to conceptualise EF when he expanded on research conducted by Vygotsky on "higher mental functions" – a set of complex cognitive processes roughly corresponding to the contemporary concept of EF (Vygotsky, 1997). Central to the Vygotsky-Luria approach was the notion that higher mental functions develop within a specific cultural-historical environment where other people including parents, teachers, and peers mediate and promote cognitive development (Kotik-Friedgut & Ardila, 2020). In the decades that followed, researchers put forth several definitions and theories of EF attempting to encapsulate these higher-level thinking processes. Thus, while several conceptualisations of EF now exist, there is general consensus among researchers that EF is comprised of three main cognitive processes including working memory, inhibitory control, and cognitive flexibility. From these stem other higher-order mental processes including planning, attention, monitoring, self-regulation, and reasoning, (Diamond, 2013; Goldstein et al., 2014). The focus of this PhD thesis will be on the development of WM and IC. This choice was motivated by previous findings in the schooling literature, in addition to several practical concerns. Research investigating schooling-related effects on EF is in its infancy, with the few available behavioural studies focusing primarily on WM and IC (ref). Nevertheless, a measure of cognitive flexibility was initially included in the thesis for completeness. However, during pilot testing it became clear that including all three measures of EF would prove too taxing for 4.5-year-olds, and thus, the cognitive flexibility measure was removed.

1.3 Theoretical accounts of the development of working memory

WM involves holding information in mind that is no longer perceptually present while simultaneously manipulating it (Diamond, 2013). WM is a vast and all-encompassing construct essential for daily functioning. It facilitates other

important cognitive skills such as planning, comprehension, reasoning and problem-solving (Cowan, 2014). The first and most widely accepted theoretical account of WM was introduced by Baddeley and Hitch (1974), when they proposed a multi-component model as an alternative to the multi-store memory model proposed by Atkinson and Shiffrin (1968). The original three-part WM model was composed of three components, each with a limited capacity: two short-term stores of domain-specific information (*phonological loop* storing verbal information and the *visuo-spatial sketchpad* storing visual information*)* and a supervisory system called the *central executive* which manipulates and controls the flow of information to and from these stores. The model was updated by Baddeley (2000) to include a fourth system, the *episodic buffer*, which integrates information across the subsidiary systems. While much of the evidence supporting the multi-component model stems from the adult literature, Gathercole, Pickering, and Ambridge (2004) examined the structural organisation of WM in children aged 4 to 15 by testing a series of models based on Baddeley's multi-component model. Specifically, several tasks representing each element of the multi-component model were administered. The authors reported broadly similar linear improvements as a function of age on all tasks. Further, in children aged 6 and up, WM performance was best described by a three-factor model capturing the phonological loop, visuo-spatial sketchpad, and central executive. Interestingly, there was high covariance between the central executive factor and the phonological and visuo-spatial sketchpad factors. However, the covariance between the phonological and visuo-spatial sketchpad factors was significantly smaller, broadly supporting the notion that the two storage systems are distinct components while the central executive controls both stores.

Another influential account of WM is Cowan's (1999) embedded-processes model, which suggests WM is a set of embedded processes where a portion of long-term memory is activated as short-term memory and held within the focus of attention. Importantly, Cowan et al. (2005) produced extensive evidence to demonstrate that, unlike earlier suggestions of seven items, the capacity of this attentional focus (and thus of WM) is limited to three to five

"chunks" of information. According to this view, increases in capacity across development are the result of improvements in the *scope of attention (*amount of information that can be stored) and *attentional control* (how information is processed). While the multi-component and embedded-processes models may seem different on a superficial level, Baddeley (2012) suggests these differences are principally ones of emphasis and terminology. Gray et al. (2017) illustrated this point when they assessed WM in 5-year-olds and tested a series of models based on: (1) Baddeley and Hitch's (1974) original three component model, (2) Baddeley's (2000) updated multi-component model, and (3) Cowan's (1999) embedded-processes model. They found that Cowan's (1999) embedded-processes model provided the best fit to the data, however, Baddeley and Hitch's (1974) original three component model also fit the data well. Thus, both models can be thought of as providing a general framework to help organise our understanding of WM.

1.4 Measures of working memory

As previously mentioned, according to Baddeley and Hitch's (1974) multi-component model, WM is divided into separate verbal and visuo-spatial systems. Numerous tasks have been developed to assess these two domains across the lifespan and reports generally indicate a linear increase in WM capacity of the sub-systems during childhood until early adulthood (Klingberg, 2006). Some researchers draw a distinction between tasks which primarily measure storage versus those which measure storage and processing. The former is sometimes referred to as short-term memory and the latter as WM. However, this distinction is not uniform across the literature and its application is inconsistent (Simmering & Perone, 2013). The current thesis considers all tasks as measuring WM but makes the distinction between simple tasks (those prioritising storage of information) and complex tasks (those combining storage + manipulation of information). For instance, the forward digit recall task is a simple verbal task that requires participants to recall a list of digits in the order they were presented, with the primary goal of assessing how effectively they can store information over a short period of time. By contrast, the backward

digit span task is a complex verbal task, requiring participants to recall a list of digits in the reverse order of encoding, necessitating concurrent processing while remembering information. Simmering and Perone (2013) conducted a large survey of empirical studies which examined developmental changes in WM capacity between the ages of 2 to 17 using a variety of tasks. Approximately 200 tasks and conditions from multiple studies across 50 papers were included. The authors divided the studies into four separate categories based on the type of task employed: simple verbal tasks, simple visuo-spatial tasks, complex backward span tasks (further categorised into verbal and visuo-spatial tasks), and other complex tasks such as those requiring further manipulation of information and/or dual-tasks (further categorised into verbal and visuo-spatial tasks). Critically, they found that across studies and domains there was a universal increase in capacity estimates across development, with older children consistently showing greater capacity estimates than younger children. However, they also found that across studies, capacity estimates varied substantially even within the same age group, suggesting that the type of task influences capacity estimations. To understand why this might be, it is necessary to discuss the theoretical perspectives on how capacity might develop.

1.5 The development of working memory

Most theories that attempt to explain WM development focus on the universal increases in capacity with age. Researchers have suggested a range of cognitive processes other than the development of WM may contribute to the increase in WM capacity, such as rehearsal (Gathercole, 1998; Halliday et al., 1990; Hitch et al., 1989; Palmer, 2000) and processing speed / efficiency (Case et al., 1982). Specifically, Case et al. (1982) examined relationships between increases in word span and increases in word repetition speed as well as between increases in counting span and increases in counting speed in adults and 6-year-old children. After controlling for processing speed between the adults and the 6-year-olds, the authors found that word spans and counting spans were no longer different between the two groups. Thus, they concluded

that the developmental improvements in WM span might reflect changes in processing speed / efficiency rather than total processing space. In other words, as children develop, basic operations become faster and more efficient, requiring less processing space and thus leading to greater capacity. Another suggestion in the literature is that age-related changes in the use of rehearsal strategies may account for improvements in WM capacity. For instance, Gathercole (1998) suggested that children become more adept at cumulatively rehearsing verbal information with increasing age. Further, studies examining either word length or phonological similarity effects have reported these effects are absent in children younger than 6- or 7-years-old, suggesting children may undergo a shift in their use of rehearsal at around this age (Halliday et al., 1990; Hitch et al., 1989; Palmer, 2000). However, more recent work has questioned this notion as researchers have reported reliable effects of phonological similarity for visually presented material when larger samples of children were tested (Al-Namlah et al., 2006; Henry et al., 2000; Jarrold & Citroën, 2013). Further, Henry et al. (2000) published a review critiquing the evidence supporting age-related changes in rehearsal strategies. They concluded that although rehearsal may improve with age, it does not play a major role in the development of verbal WM capacity. This is in agreement with Cowan (2016), who argued that although age-related increases in factors such as rehearsal and processing speed may play a role in WM performance, a single-cause explanation does not account for all the observed variance in capacity development.

Providing a comprehensive account of how capacity develops is further complicated by conflicting reports in the developmental visual WM (VWM) literature, particularly in studies examining VWM capacity in infants and children. While infants cannot verbally report memory, several techniques have been developed to measure their capacity. For instance, the delayed response task is an example of a standard reaching paradigm, where an item is hidden from the infant who is then allowed to search for the item after a time delay (Simmering, 2016). Capacity in this task is measured as the number of objects the infant can remember as well as the length of time the items can be

remembered for. Findings from reaching paradigms have reported infants are able to remember the location of items by 5.5 months, with a linear increase in how long this information can be held in VWM (Simmering, 2016). A primary limitation of reaching paradigms is that they are rarely used to provide an estimate of capacity beyond 18 months of age, and thus have not been used to study working memory in childhood (Simmering, 2016). An alternative method to assess infant capacity is through the use of looking paradigms, which rely on infants' tendency to preferentially look at novel stimuli. Robert Fantz (1964) pioneered this research by presenting infants with a series of images, one on the left and one on the right, and the amount of time infants spent looking at either image was recorded. Fantz (1964) found that, if one image was changed and the other stayed constant, infants would preferentially look at the changing image. Thus, this "novelty preference" was taken as evidence to suggest the infant had developed memory for the familiar image (Buss et al., 2018).

Following on from this work, Ross-Sheehy et al. (2003) developed the change-preference task to estimate VWM capacity in infants. Specifically, infants were shown two simultaneous displays of flashing coloured squares. On one monitor the colours of the flashing squares remained constant, while on the other monitor the colour of one of the flashing squares was changed in each new presentation. The authors reported that 6-month-olds showed preferential looking for up to one changed item, while 10-month-old infants showed preferential looking for up to four changed items. Thus, the authors concluded VWM capacity increases from one to an adult-like four items between the ages of 6- and 10-months-old. This change-preference paradigm was developed based on the change-detection paradigm (Luck & Vogel, 1997) commonly used to assess VWM in older children and adults. Here, subjects are shown an array of coloured items, followed by a brief delay, and then by a second array of coloured items. The second array is either identical to the first array, or the colours of one of the items will have changed. Thus, subjects must decide whether the two arrays were the same or different. Using this task Riggs et al. (2006) reported that capacity was 1.52 items at 5-years-old, 2.89 items at 7-years-old, and 3.83 items at 10 years-old. Simmering (2012) expanded on

these findings and reported capacity increases from two to three items between the ages of 3 and 5, to approximately four items by age 7. Taken together, these findings paint a contradictory picture of VWM capacity across development. Several explanations have been put forth to account for the contradictory findings between the infant change-preference task and the child change-detection paradigm. For instance, Riggs et al. (2006) proposed three reasons for the discrepancies in capacity estimates: (1) the change-preference task may not be measuring VWM capacity, (2) the change-preference task is a passive measure and does not tap into the same type of VWM and (3) VWM is fixed during infancy and the development in childhood is due to other cognitive factors besides capacity. However, more recent work by Perone et al. (2011) suggests the change-preference task might overstate capacity estimates. Specifically, these researchers simulated infant's performance using a model of infant looking and memory. Critically, they found that preference for the changing display did not require memory for all the items in the display, with the model producing higher capacity estimates than the number of items maintained in WM. Consequently, Simmering (2012) suggests that both the change-preference and change-detection tasks rely on the same underlying VWM system, but that the different task structures and behavioural measures lead to different capacity estimates. Building on this idea, Simmering (2016) brought together the change-preference and change-detection tasks into a single computational framework (the dynamic model) to demonstrate how the same cognitive processes give rise to different capacity estimates. Critically, Simmering (2016) proposes WM capacity is a dynamic process that emerges from a unified cognitive system that flexibly adapts to the demands and context of each task.

While the computational details of the dynamic model are beyond the scope of this thesis, the main features are useful to discuss in terms of VWM development. The dynamic model falls within the broader dynamic system theory, where focus is on how behaviour emerges from multiple underlying causes such as the task demands, the details of the environment, and the history of the organism (Simmering, 2016). Using this framework, Simmering

(2016) tested several hypotheses: (1) capacity estimates from the change-preference task should continue to increase across development beyond the 4 items reported by Ross-Sheehy et al. (2003) at 10 months, (2) capacity estimates from the change-preference task should be higher than estimates from the change-detection task within the same participants, (3) although capacity estimates differ, performance should be correlated across tasks as they rely on the same underlying VWM system, and (4) implementing the real-time stability hypothesis (i.e., that developmental improvements arise from increasing stability in the VWM system) in the dynamic model can capture developmental improvements in both tasks. Three behavioural experiments were conducted which demonstrated that as predicted, change-preference scores continued to increase in childhood, reaching a capacity of at least 6 by age 3. Further, when the same participants were tested using the change-detection task, capacity estimates were significantly lower. Lastly, when comparing performance across the two tasks, capacity estimates from the change-detection were significantly and independently predicted by set size two and switch rates from set size six in the change-preference task, even after controlling for age related improvements. To address the fourth prediction, Simmering (2016) conducted a series of simulations and found the dynamic model showed good fit to the empirical data, providing support for the proposed developmental mechanism, namely, increases in real time stability through strengthening connectivity. Further, an analysis of the processes within the model revealed how changes in connectivity give rise to seven characteristics of real-time stability which contribute to changes in performance over development, including: strength of representations, encoding speed, resistance to interference, decay, capacity limits, correspondence between memory and behaviour across tasks, and effects of task context on memory. Thus, a primary advantage of Simmering's (2016) dynamic model is that it provides a comprehensive account of how several factors contribute to developmental change in WM rather than searching for a single cause explanation of capacity development.

1.6 Neural network underlying working memory development

While most of the research into WM has been caried out at the cognitive level, technical advances in modern neuroimaging techniques have provided us with the means to investigate the neural networks underlying WM. Non-invasive neuroimaging furthers our understanding of cognition by revealing universal principles of functional brain organisation as well as how brain function varies across individuals (Gabrieli et al., 2015). Early neuroimaging studies of WM involving non-human primates used spatial-delayed-response tasks and found that the neurons in the PFC fired only during the delay period of the task, suggesting they were involved when the stimuli was no longer perceptually present (Fuster & Alexander, 1971). This finding popularised the notion that the PFC was the neural system responsible for the storage of information in WM (Courtney et al., 1998; Funahashi et al., 1993; Goldman-Rakiv et al., 2000; Haxby et al., 2000; Mottaghy et al., 2002). However, other researchers have challenged this account, citing studies that found WM abilities were not impaired in humans with large PFC lesions (D'Esposito & Postle, 1999). In line with this, several neuroimaging studies on healthy patients have failed to find any evidence for a segregation-by-domain of PFC WM activity (Arnott et al., 2005; D'Esposito & Postle, 1999; Bradley, Postle & D'Esposito, 1999; Stern et al., 2000). Based on these findings, Postle (2006) proposed that, instead of a specialised PFC based WM storage system, WM is a property that emerges from a cognitive system that can represent different types of information and is endowed with flexibly deployable attention. A similar view has been proposed by Christophel et al. (2017), who suggests that WM relies on the interplay between sensory regions in the posterior cortex and more frontal regions. Taken together, findings from the adult neuroimaging literature suggest WM is not a unitary construct, but rather, a coordinated system involving a distributed network of brain regions.

Given the added complexities associated with conducting neuroscientific investigations on children, less is known about the neural networks underlying the development of WM. However, early functional magnetic resonance imaging (fMRI) work conducted by Casey et al. (1995) revealed that activity in

the dorsolateral pre-frontal cortex (dlPFC) that supports WM performance in adults also supported WM performance in 9- to 11-year-old children. Thus, Casey et al. (2000, 2005) theorised that the frontal cortex undergoes fine-tuning and strengthening of synaptic connections which contributes to WM development across childhood. Following on from this research, Kwon et al. (2002) examined children and adults ranging from 7- to 22-years-old while they completed a visuo-spatial WM task and found age-related increases in brain activation in focal regions of the bilateral dlPFC, left ventrolateral PFC, left premotor cortex, and bilateral posterior parietal cortex (PPC). Further, Crone et al. (2006) administered an object WM task to three age groups (8- to 12-year-olds, 13- to 17-years-olds, and 18- to 25-years-olds) and found that across participants, activation levels in the dlPFC and superior parietal cortex (but not the ventrolateral PFC) were positively correlated with performance, suggesting increased recruitment of these areas is associated with better WM. These findings are in agreement with several other cross-sectional studies that have reported an increase activity in frontal and parietal regions across development, and have associated this with better WM performance (Klingberg et al., 2002; Satterthwaite et al., 2013). Thus, while several studies have suggested that improvements in WM are the result of the gradual maturation of the fronto-parietal network, the cross-sectional nature of the research has only allowed for correlations between current cognitive ability and current structure and/or activity. Tamnes et al. (2013) improved upon this limitation by conducting a longitudinal study to formally test the relationships between improvements in verbal WM and structural brain changes in children and adolescents ranging from 8 to 22-years-old. They reported improvements in WM were related to a reduction in cortical volume in the bilateral prefrontal and parietal regions, providing the first direct evidence that structural maturation of the fronto-parietal network supports WM development. Similarly, Darki and Klingberg (2015) assessed visuo-spatial WM in children and adults aged 6- to 25-years-old across two years and found white matter tracts and caudate activity predicted future WM capacity.

As is evidenced by the age ranges selected in the studies discussed above, the neurodevelopmental literature employing fMRI has been limited to studying children over the age of six. fMRI scanners are noisy and require the participant to lie extremely still for long periods of time, an obstacle for young children. However, more recent applications using fNIRS have allowed researchers to record functional neural activation in young children as well as in infants. fNIRS overcomes many of the challenges associated with fMRI as it is much more tolerant of movement and relatively quick to setup. While fNIRS is limited to recording from cortical regions, several studies have employed fNIRS and found comparable results to fMRI research. For instance, Buss et al. (2014) used fNIRS to record from the bilateral frontal and parietal regions in 3- and 4-year-old children while they completed a VWM task. They reported similar task-related activation across the fronto-parietal network implicated in previous child and adult fMRI investigations. Specifically, they found a developmental increase in activation where 4-year-olds showed more robust parietal activation across set size than 3-year-olds. Another fNIRS study conducted by Tsujimoto et al. (2004) compared frontal activation between 5 and 6-year-old children and adults while they completed a spatial WM task. They reported that similar regions were activated by the children and the adults, suggesting children recruit a similar network to adults. Lasty, Perlman et al. (2016) used fNIRS to record from frontal and parietal regions while 3- to 7-year-old children completed a spatial WM task. They found developmental improvements in WM were associated with an increase in activation in the bilateral PFC. Further, they reported an increase in activation in these regions when they increased the delay period of the task. Taken together, findings from both the fMRI and fNIRS neurodevelopmental literature have highlighted a distributed network of frontal and parietal brain regions important for WM processing. Critically, increased activation in these regions is associated with increases in age, task demands, and task performance.

1.7 Individual differences in working memory development

Individual differences in WM abilities are associated with a range of outcomes including fluid intelligence (Fukuda et al., 2010), cognitive function (Johnson et al., 2013), and most notably, educational attainment (Alloway & Alloway, 2010; R. Bull & Scerif, 2001; Gathercole, Pickering, Knight, et al., 2004; Swanson & Beebe-Frankenberger, 2004). Specifically, Alloway and Alloway (2010) assessed verbal WM in 4- to 5-year-old children and found WM predicted numeracy and literacy skills 6 years later. Further, they reported that WM accounted for a greater portion of the variance than IQ did. Deficits in WM have also been linked to poorer educational outcomes (Alloway et al., 2009; Gathercole & Alloway, 2008; Pimperton & Nation, 2014), greater learning difficulties (Swanson & Ashbaker, 2000; Szucs et al., 2013) as well as certain developmental disorders such as attention deficit hyperactivity disorder (ADHD - Martinussen et al., 2005; Willcutt et al., 2005). Thus, identifying the sources of these individual differences is of critical importance for furthering our knowledge of WM development and ensuring interventions can be developed to help children with deficits in WM.

1.7.1 Characteristics of the child

While increases in WM are certainly the result of increasing age and brain maturation, regulatory processes such as temperament characteristics have also been associated with individual differences in WM development. Wolfe and Bell (2004) investigated age-related differences in pre-schooler's EF (using a composite WM and IC measure) and related these differences to temperament characteristics. Specifically, EF was assessed in three groups of children aged 3.5, 4, and 4.5-years-old. The authors reported positive associations between EF and effortful control in the 3.5- and 4-year-old children, while negative associations between EF and surgency were found in the 4.5-year-olds. Effortful control in this study was derived from subscales including low intensity pleasure, inhibitory control, attentional focusing, and perceptual sensitivity while surgency was derived from subscales including impulsivity, high intensity pleasure, activity level, positive anticipation, and a negative contribution of

shyness. The authors suggested EF might be important early in development, but as these skills improve with age they begin to play less of a role in the control of behaviour. Another study conducted by Visu-Petra et al. (2018) investigated relationships between temperament and WM in 4- to 7-year-old children. They reported that, in addition to age-related improvements in WM overall, greater visuo-spatial WM was predicted by higher effortful control and lower impulsivity while both verbal and visuo-spatial WM were predicted by lower impulsivity. Taken together, these findings suggest that temperament characteristics significantly contribute to the variance in WM development. In addition to the internal factors which might contribute to WM development, certain environmental factors have also been associated with individual differences in WM.

1.7.2 Role of the home environment

The home environment has been the focus of much research for its critical role in neurocognitive development, especially in infants and young children who rely entirely on their parents for support. The home environment is an umbrella term used to describe a set of variables relating to the environment a child is reared in. Numerous models have been proposed that attempt to conceptualise the home environment and how it might shape development (Kininmonth et al., 2021). However, the complex and multi-faceted nature of the home environment means a variety of different measures have been developed, each measuring slightly different aspects. Nevertheless, broadly speaking, measures of the home environment usually consist of (1) physical aspects such as safety of play areas, household possessions, cleanliness and (2) social aspects such as quality of parent-child interactions, family size / structure, provision of stimulating learning experiences (Leventhal & Brooks-Gunn, 2001). A common way to assess the home environment is through the Home Observation for Measurement of the Environment (HOME) inventory (Caldwell & Bradley, 2003), which combines interview questions with direct observations to measure the quality of the childrearing environment. Fishbein et al. (2019) administered the HOME inventory alongside six measures of EF in 8- to 11-year-old children

and found that positive aspects of the home environment predicted better performance on two measures of EF, namely, visual information processing and working memory. Similarly, Sarsour et al. (2011) administered the HOME inventory alongside three tasks of EF assessing working memory, inhibitory control, and cognitive flexibility to 8- to 12-year-old children and found that a more positive home environment was associated with better performance in all three tasks. Sarsour et al. (2011) also examined associations between EF and another aspect of the child's environment, family socio-economic status (SES), a multidimensional construct consisting of factors such as parental income, education, and occupation (McLoyd, 1998). They found that children from higher SES backgrounds performed better on all three EF tasks. Further, they reported that two subscales of the HOME inventory including "enrichment activities" and "family companionship" mediated the relationship between family SES and WM. Specifically, "enrichment activities" measured the extent to which parents use family and community support to enrich their child's development while "family companionship" measured the extent of parental involvement in child activities leading to mutual enjoyment. Thus, these findings highlight the importance of psychosocial and parenting factors in contributing to the mechanisms underlying the relationship between SES and WM.

In addition to the robust associations found between the home environment, SES, and cognitive function, the neurodevelopmental literature has reported significant associations between SES and structural brain development (Brito & Noble, 2014; Hackman & Farah, 2009; Hair et al., 2015; Noble et al., 2012, 2015; Tomalski et al., 2013). Specifically, family income has been associated with smaller sized frontal lobes as well as a reduction in grey matter in the frontal and parietal cortices by the age of 4-years-old (Hanson et al., 2013). While the relationships between the home environment / SES and brain structure are well documented in the literature, only a handful of studies have examined how these variables may be related to brain function underlying WM. For instance, Maguire and Schneider, (2019) used electroencephalogram (EEG) to compare electrical resting states in children aged 8 to 15 from high SES and low SES homes. They found that children from low-income homes

showed greater resting theta power, which in turn was related to worse WM. Another study conducted by Wijeakumar et al. (2019) recorded fNIRS activation on infants in rural India while they completed a change-preference task. The authors reported that children from low-income families showed weaker brain activity and poorer distraction suppression in the left frontal cortex. Thus, based on the review above, a child's home environment and family SES status undoubtedly plays a large role in the developmental trajectory of WM. However, another specific environmental factor which requires careful examination is schooling.

1.7.3   Role of the schooling environment

Given that, second to the home, children spend most of their time in school, it is reasonable to assume the schooling environment plays a significant and influential role in children's development. Schools not only increase the acquisition of knowledge and skills but also foster social and emotional growth (Meece & Eccles, 2010). Although robust associations between WM and scholastic achievement have been reported in the literature (Alloway & Alloway, 2010; Bull & Scerif, 2001; Gathercole, Pickering, Knight, et al., 2004; Swanson & Beebe-Frankenberger, 2004), relatively few studies have attempted to isolate the unique contributions of schooling to WM development. This may be in part due to the challenges associated with assessing the causal impact of schooling. Specifically, most individuals living in the developed world will experience some degree of schooling during childhood, making experimental comparisons between those who attend school and those who do not impossible. Thus, much of the research into schooling-related effects on WM development has been largely correlational in nature. For instance, Roberts et al. (2015) examined the extent to which chronological age and schooling duration were associated with verbal and visuo-spatial WM in 6- to 7-year-old children. Children were recruited from several different schools in Australia and each school was quasi-randomly assigned to one of the four school terms. The authors reported that WM scores steadily improved across the year, with children who were assessed during the fourth term performing significantly

better than those who were assessed during the first term, even after adjusting for age and other potential confounds. Thus, the researchers concluded the development of WM is associated with the amount of time children have spent in the classroom, above and beyond their chronological age. Similarly, Finch (2019) examined whether WM skills grew more during the school year or during the summer months by assessing WM in American children enroled in either their first, second, or third year of school. Results showed children's WM skills grew more during the school year than during the summer, suggesting the school environment provides unique opportunities for children to improve their WM. Interestingly, another correlational study conducted by Souza-Talarico et al. (2007) in Brazil found that a higher level of schooling was associated with better WM performance in older adults, suggesting the benefits associated with schooling duration may persist even into adulthood. To overcome some of the confounds associated with correlational research, some researchers have conducted cross-cultural studies, where traditionally schooled children are compared to non-schooled children from other cultures. These studies have reported major differences between the two groups of children in several domains including verbal WM (Cole et al., 1971). However, disentangling cross-cultural and societal differences from schooling differences has proven difficult, limiting the strength of the conclusions that can be drawn from these studies (Christian et al., 2001).

The limitations associated with correlational and cross-cultural research can be greatly minimised through the use of quasi-experimental designs which allow for more causal investigations into schooling-related effects on development. For instance, an innovative quasi-experimental technique called the school-cut off design relies on the fact that most school districts use an arbitrary cut-off based on a child's date of birth to determine eligibility for school enrolment. Using this design, researchers can compare children whose birthdates fall shortly before the cut-off (and are therefore enroled into school) with children whose birthdates fall shortly after (and are therefore not enroled into school). By conducting longitudinal assessments at the start and at the end of the year, children's growth across the year can be measured. Further, since

both groups of children are similar in age but differ in year of school entry, any differences in observed growth can be attributed to schooling. Although the school-cut off design has been used and found a positive effect on numeracy (Bisanz et al., 1995; Christian et al., 2000) and literacy skills (Frederick J. Morrison et al., 1995; Varnhagen et al., 1994), only one study has so far applied the method to examine WM. Specifically, Burrage et al. (2008) administered tasks assessing response inhibition and working memory in a sample of American children and found children who attended school had better WM at the end of the year than children who stayed in kindergarten. However, these findings should be interpreted with caution as the schoolers also outperformed the kindergartners at the start of the year, and this was not controlled for in their analyses. Specifically, the analysis did not compare the mean *change* within each group, and thus is it unclear whether the growth shown by the schoolers was greater than the growth shown by the kindergartners. If the schooling environment did in fact increase WM skills, children who went to school should have shown greater change across the year than the kindergartners.

1.8 Summary

WM is an essential cognitive construct necessary for daily functioning. Numerous tasks have been developed to assess WM across the lifespan and most research has pointed to a linear increase in WM capacity during childhood until early adulthood (Klingberg, 2006). Findings from the neurodevelopmental literature have implicated a broad network of frontal and parietal brain regions important for WM processing (Buss et al., 2014; Kwon et al., 2002; Perlman et al., 2016). Critically, increased activation in these regions is associated with increases in age, task demands, and task performance. Several factors have also been shown to contribute to the developmental trajectory of WM including individual characteristics of the child, home environment and parental factors, as well as schooling. However, the nature of these associations and the relative contributions of each is not well understood. Thus, Chapter 2 will probe the association between VWM performance, brain function, and temperament and parental factors in a sample of 4.5-year-old pre-school children. Specific

research aims and hypotheses, as well as the rationale for the research is presented in Chapter 2 (section 2.2). Chapter 3 attempts to reconcile previous methodological and interpretational issues and fill in the knowledge gap surrounding the relationship between WM, formal schooling, and academic success. Using a modified cut-off design, Chapter 3 investigates whether the first year of schooling results in an improvement in VWM performance and underlying changes in brain activation and determine whether this is associated with an improvement in academic performance. An in-depth review of the literature as well as the research aims, hypotheses, and rationale for the research is presented in Chapter 3 (section 3.2).

1.9 Theoretical accounts of inhibitory control

IC refers to the ability to control one's thoughts, behaviours, attention, and emotions in order to inhibit a dominant response in favour of a more necessary or appropriate one (Diamond, 2013). The concept of IC has been used to explain a range of cognitive processes, and consequently, early models of inhibition were often piecemeal. Theorists such as Nigg (2000) therefore attempted to provide an overarching framework of IC, and suggested inhibition is comprised of a set of functions rather than a single unitary construct. Specifically, Nigg (2000) adopted a "splitter" viewpoint to outline eight kinds of inhibition, which fall under either executive inhibition, motivational inhibition, or automatic inhibition. Executive inhibition encompasses 4 types of effortful inhibition including interference control (prevents interference due to resource or stimulus competition), cognitive inhibition (suppresses nonpertinent ideation to protect working memory/attention), behavioural inhibition (suppresses prepotent response), and oculomotor inhibition (effortfully suppress reflexive saccade). Motivational inhibition is split into response punishment cues and response to novelty, and lastly, automatic inhibition involves suppressing recently inspected stimuli for attention / oculomotor saccade and suppressing information at unattended locations while attending elsewhere.

Nigg's (2000) classification was based primarily on conceptual distinction, however, while such inhibitory related processes may be conceptually distinguishable, Friedman and Miyake (2004) suggested these processes may in fact reflect the same underlying cognitive abilities. Friedman and Miyake (2004) therefore tested the distinctions between three inhibition-related functions they termed pre-potent response inhibition (combinations of Nigg's (2000) behavioural and oculomotor inhibition), resistance to distractor inference (similar to Nigg's (2000) interference control), and resistance to proactive interference (similar to Nigg's (2000) cognitive inhibition). Specifically, Friedman and Miyake (2004) defined pre-potent response inhibition as the ability to deliberately suppress dominant responses, and resistance to distractor interference as the ability to resist or resolve interference from information in the external environment that is unrelated to the task at hand. Lastly, resistance to proactive interference was defined as the ability to resist memory intrusions from information that was previously relevant to the task but has become irrelevant. Critically, they found that pre-potent response inhibition and resistance to distractor inference were correlated, and thus, despite the distinct classification suggested by Nigg (2000), these inhibition abilities are related. Friedman and Miyake (2004) took this as evidence for a "common inhibition ability" and suggested that pre-potent response inhibition and resistance to distractor inference share the same underlying requirement of actively maintaining goal-related information. However, Friedman and Miyake (2004) did not include any measures of WM capacity, and thus, the proposed common reliance of pre-potent response inhibition and resistance to distractor interference on active goal maintenance was not explicitly tested. The authors also found that these two inhibition constructs were not related to resistance to proactive interference, suggesting cognitive inhibition may in fact be a separable inhibition function.

During a more recent review of the literature, Diamond (2013) suggested IC could be divided into three main subcomponents which include cognitive inhibition (suppressing prepotent mental representations), attentional inhibition (selectively attend and suppress attention to other stimuli), and behavioural

inhibition (controlling behaviour and emotion). Cognitive inhibition and attentional inhibition are the mechanisms underlying interference control and thus involve suppressing prepotent representations based on one's goals or intentions. On the other hand, behavioural inhibition involves self-control, defined as (1) resisting temptations and not acting impulsively and (2) having the discipline to stay on task despite distractions.

1.10 Measures of inhibitory control

Over the last few decades, several tasks have been developed which tap into the different inhibition-related functions highlighted above. For instance, response inhibition is generally assessed using non-selective stopping tasks such as the stop signal (Logan, 1994), the go/no-go, and the antisaccade (Hallett, 1978) task. While each of these tasks involves different stimuli and rules, the primary requirement is for participants to intermittently suppress a motor response after the presentation of a conditional stimulus or cue (Tiego et al., 2018). For instance, during a standard go/no-go task, participants must execute a motor response when presented with "go" stimuli but inhibit this response when presented with "no-go" stimuli. Thus, a common way to measure response inhibition is through the number of commission errors (i.e., responding to a no-go stimulus) as this indicates a failure to inhibit a response. Resistance to distractor interference (also commonly referred to as attentional inhibition/ interference control / interference suppression in the literature) is usually assessed using tasks where the primary goal is to select visual targets that were presented alongside irrelevant distractors. Examples of these tasks include the word naming task (Kane et al., 1994), and the shape naming task (DeSchepper & Treisman, 1996). For instance, in the shape naming task, participants must indicate whether a white shape matches a green shape that is either presented alone or alongside a distractor shape. Given the substantial overlap between response inhibition and attentional inhibition identified by Friedman and Miyake (2004), there are also several tasks that are used interchangeably to measure both of these inhibition constructs. Examples

including the Stroop task (Stroop, 1935), the Erikson Flanker task (Eriksen & Eriksen, 1974), and the Simon task (Simon, 1969), which are a set of stimulus response compatibility tasks where the participant must selectively attend and respond to target stimuli while ignoring distracting information / response options (Tiego et al., 2018). For example, during the Stroop task, participants must name the colour in which colour words and neutral words are presented, while suppressing the tendency to read out the word.

An advantage of the tasks described above is the majority can be easily adapted to be used with young children. For instance, child-friendly stimuli can be used, and difficulty level can be controlled by altering the stimulus presentation time and duration of response time. However, additional tasks have also been developed to be used specifically with young children. Garon et al. (2008) made the distinction between "simple" and "complex" inhibition tasks which are classified according to WM demands. Tasks measuring simple response inhibition often involve withholding or delaying a prepotent response and have even been used to measure inhibition in infants (Kochanska et al., 1996, 1998). Examples include "don't" paradigms where children must suppress a rewarding behaviour and "delay" paradigms where they must delay gratification. On the other hand, child-friendly versions of the Simon task, Flanker task, and go-no/go task are a few examples of complex response inhibition tasks, as these tasks require the child to hold a rule in mind and respond according to this rule, while simultaneously inhibiting a prepotent response (Garon et al., 2008).

1.11   The development of inhibitory control

Response inhibition has probably been the most extensively studied component of IC in the developmental literature due to the wealth of tasks available. As previously mentioned, developmental researchers often make the distinction between simple (low WM demand) and complex (high WM demand) tasks. Simple tasks are most commonly used to measure response inhibition in infants and toddlers. For instance, using the don't paradigm (i.e., child is told not to

play with a toy), Kochanska et al. (1998) found 8-month-old infants were able to inhibit their behaviour 40% of the time. In a follow-up study, Kochanska (2002) found this increased to 78% and 90% of the time for 22-month and 33-month-old infants, respectively. Another example of an inhibition task that has been adapted to be used with children is the antisaccade task. In the standard version, participants must inhibit a reflexive saccade to a lateral stimulus in favour of a subdominant response to the contralateral side (Garon et al., 2008). Using a modified version of the antisaccade task suitable for infants, Johnson (1995) found 4-month-old infants could inhibit a reflexive saccade, however, they were unable to execute a saccade to the contralateral side. In fact, further research conducted by Scerif et al. (2004) found that it is not until children are between 12- and 18-months-old that they are able to inhibit the automatic response and produce an antisaccade. More recently, using the delay paradigm, Carlson (2005) reported age-related increases from 24-months to 4-years-old in the length of time children were able to delay. Specifically, 50% of 24-month-olds delayed eating a treat for 20 seconds, 85% of 3-year-olds suppressed the urge for 1 minute, and finally, 72% of 4-year-olds suppressed the urge for 5 minutes. In another version of the delay task, children are told they can choose between a small reward now or wait for a larger reward later. Using this task, several studies have reported age-related increases between the ages of 3 and 5 in the number of children who choose to wait for the larger reward (Lemmon & Moore, 2007; Moore et al., 1998; Thompson et al., 1997). Thus, by using variations of these simple tasks, researchers have found steady age-related improvements in response inhibition from infancy to early childhood.

Given that complex inhibition tasks involve larger WM demands and require some verbal control of behaviour, they are most often used to assess response inhibition in children above the age of three. The literature has also reported that, as children get older, they are able to complete tasks that involve a greater degree of conflict. Specifically, Rueda et al. (2005) suggested the ability to resolve conflict develops slowly in the first 2 years of life followed by rapid improvements between the ages of 2 and 5. Evidence to support this

notion is demonstrated by Carlson (2005), who administered a modified version of the Stroop task called the reverse categorization task, where children must first sort small items into a small bucket and large items into a large bucket and then sort in the opposite way. They found that while only 20% of 2-year-olds could successfully complete the task, 85% of 3-year-olds were successful. This is further supported by longitudinal research conducted by Hughes and Ensor (2007), who administered the Stroop task and found significant improvement between the ages of 2- and 4-years-old.

The literature examining age-related improvements in inhibition above the age of 5 has been somewhat more mixed (Best & Miller, 2010). For instance, Klenberg et al. (2001) examined a broad age range and found improvements in two tasks assessing inhibition between the ages of 3 and 6, but no further improvements between the ages of 6 and 12. However, this might be due to the fact that the tasks employed in this study measured a basic capacity to inhibit impulses and were likely too easy for the older children. This reflects a limitation of the literature, as selecting appropriate tasks that are well-suited to examining developmental trends can be challenging. Interestingly, the go/no-go task, while first developed to be used with adults, overcomes this challenge and has been successfully used to investigate developmental change across a broad range of ages (Brocki & Bohlin, 2004; Johnstone et al., 2007; Jonkman, 2006; Lewis et al., 2017). Specifically, Brocki and Bohlin (2004) compared performance on the go/no-go task in four age groups including 6- to 7.5-year-olds, 7.6- to 9.5-year-olds, 9.6- to 11.5-year-olds, and 11.6- to 13.1-year-olds. They found age-related improvements in a combined disinhibition score between the second and third age groups, with the latter performing significantly better than the former. Likewise, Lewis et al. (2017) examined children between the ages of 6 and 11 both cross-sectionally and longitudinally. They found that cross-sectionally, the 6- to 7-year-old group made more commission errors (incorrect responses to no-go stimuli) than the 8- to 9-year-olds and the 10- to 11-year-olds. Further, the 8- to 9-year-olds also made more commission errors than the 10- to 11-yearolds. Lastly, when examining the longitudinal data, Lewis et al. (2017) reported that all children (regardless of

age) made significantly lower commission errors at the second timepoint compared to the first timepoint. On the other hand, Jonkman (2006) failed to find any significant differences in commission errors between 6- to 7-year-old and 9- to 10-year-old children. However, they did find significant differences between both groups of children and young adults. Similarly, Johnstone et al. (2007) examined go/no-go task performance in 7- to 12-year-old children and found the probability of successfully inhibiting a response to a no-go trial did not improve with age. Interestingly, Cragg and Nation (2008) used a modified version of the go/no-go task that allowed for partial commission errors in addition to traditional commission errors. Using this paradigm, they found that only the partial commission errors were sensitive to age-related improvements in 5- to 7-year-old and 9- to 11-year-old children, suggesting stage of execution may be a factor in inhibition difficulty. Taken together, these findings suggest that inhibition appears to develop rapidly in the pre-school years and by age 4, children show signs of successful response inhibition in both simple and complex tasks (Best & Miller, 2010). While inhibition continues to improve in middle childhood, Best and Miller (2010) argue these improvements do not reflect fundamental changes in cognition, but rather, refinements involving quantitative improvements in accuracy and increasing efficiency in overriding a prepotent response. A potential way to gain further insight into these more subtle refinements is through the use of neuroimaging techniques. Critically, examining the neural networks underlying inhibitory development could be particularly helpful when neural changes precede changes in behaviour.

1.12   Neural networks underlying inhibitory control development

A common method used to examine the neural networks underlying IC development is EEG, a non-invasive monitoring modality which measures the brain's electrical activity. A primary advantage of EEG is that it can be reliably used to measure brain activity across the lifespan, from infancy to adulthood. For instance, Bell et al. (2007) conducted longitudinal EEG research spanning from infancy to middle childhood and found successful performance on the A-not-B task in infants was associated with an increase in activity relative to

baseline at multiple anterior and posterior scalp locations, while successful performance on the day/night Stroop task at 4.5-years-old was associated only with increased medial frontal activity. Further, by age 8, brain activity became more focused in the right frontal region, suggesting a shift from global to localised brain activity may underly developmental improvements in response inhibition (Best & Miller, 2010). This developmental shift from global to more localised brain activity is further demonstrated by Jonkman (2006) who compared EEG measured brain activity in two groups of children (aged 6 to 7 and 9 to 10) and young adults (aged 19 to 23) while they completed a go/no-go task. These authors focused on two main electrophysiological components which have been previously associated with the go/no-go task in the adult literature: the N2 and the P3. The N2 is a negative deflection over the frontocentral regions and is consistently found to be more robust in response to no-go than to go trials (Cheng et al., 2019). The P3, a positive deflection, can be observed in the parietal region in response to go trials and the frontocentral regions in response to no-go trials (Cheng et al., 2019). Specifically, Jonkman (2006) found a decrease in the no-go N2 amplitude across fronto-parietal regions, with the largest decrease occurring between the ages of 6 and 10. However, no behavioural improvements in the ability to inhibit were found during this same period. Similarly, Hoyniak (2017) conducted a meta-analysis of 65 studies that assessed response inhibition in children aged 2 to 12 using the go/no-go task and found the N2 was larger in response to no-go trials than to go trials and decreased in amplitude / latency across childhood. In line with this, Mehnert et al. (2013) used fNIRS to compare activation in children aged 4 to 6 and adults during a go/no-go task. They found both groups showed an increase in activation in response to no-go trials than to go trials, with children showing greater activation than adults for both trial types.

Given the challenges associated with placing young children in fMRI scanners, there are significantly fewer studies that have used fMRI to investigate the early development of response inhibition. Nevertheless, the few studies which have used fMRI have reported comparable results to EEG work. For instance, Casey et al. (1997) conducted one of the first fMRI investigations

into response inhibition development by administering a go/no-go task to a sample of children aged 7 to 12 and adults. They found that, while children and adults activated similar regions in response to no-go trials, children showed a greater volume of activation in the dorsal and lateral PFC. Durston et al. (2002) conducted an fMRI study on a sample of children aged 6 to 10 and adults and found similar results. Both children and adults showed greater activation for no-go trials compared to go trials in the bilateral ventral PFC, the right dlPFC, and the right parietal lobe. Further, the magnitude of this difference was greater for children than for adults suggesting that although children recruited the same neural circuitry as adults, they did so less efficiently by activating these regions to a greater extent.

Taken together, findings from both the fMRI and EEG literature suggest global, more diffuse brain activation in early and middle childhood. With development, this pattern of activation becomes more efficient and localised to specific areas including the PFC and parietal lobe. Interestingly, behavioural improvements in task performance do not always parallel these developmental changes in neural activity, as several of the studies highlighted above failed to find behavioural improvements in response inhibition. Thus, these dramatic changes in neural activity may only lead to subtle changes in behaviour including refinements in accuracy and efficiency (Best & Miller, 2010).

1.13   Individual differences in inhibitory control development

The role of individual differences in IC development has attracted significant attention from developmental researchers given its widespread implications for future academic achievement (Blair & Razza, 2007; Gawrilow et al., 2014; McClelland et al., 2014; Smith-Donald et al., 2007; Son et al., 2019) and psychosocial functioning (Anzman-Frasca et al., 2015; Eisenberg et al., 2001; Rhoades et al., 2009; Shoda et al., 1990). For instance, Blair and Razza (2007) examined the role of self- regulation in relation to emerging academic abilities in 3- to 5-year-old children. While several aspects of self-regulation predicted certain academic outcomes, IC made independent contributions to all three

measures of academic ability (mathematical knowledge, letter knowledge, and phonemic awareness). The authors suggested that the ability to inhibit distracting or irrelevant information while reading or when faced with a numerical problem may be a contributing factor to success, over and above specific knowledge of problem solutions. For example, IC may allow children to consider multiple dimensions of a problem, rather than focusing on the most salient or recent aspects. Further, deficits in inhibition have been implicated in behavioural disorders in childhood such as ADHD (Berlin et al., 2003) and autism (Geurts et al., 2014). Given that children vary considerably in their inhibitory capacity (Carlson & Wang, 2007; Troller-Renfree et al., 2019), investigating the sources of these individual differences could provide further insight into the development of IC and potentially identify those who may be at risk for developmental disorders.

1.13.1 Child characteristics

Given the conceptual similarities between inhibitory control and emotional control, it is not surprising individual differences in inhibition have been linked to regulatory dimensions of temperament (Aksan & Kochanska, 2004; Carlson & Wang, 2007; Gerardi-Caulton, 2000; Hongwanishkul et al., 2005; Kochanska et al., 1997; Wolfe & Bell, 2004). For instance, Wolfe and Bell (2004) assessed inhibition and temperament in 4.5-year-old children using the day/night Stroop task, the yes/no task, and the Children's Behavioural Questionnaire. They reported positive associations between inhibitory performance and two out of the four subscales that comprise the effortful control factors of the questionnaire. Specifically, task performance was positively associated with attention focusing and inhibitory control but not with low sensitivity pleasure and perceptual sensitivity. The authors argued the association only existed for attention focusing and inhibitory control as these two subscales draw more heavily on the cognitive component of the effortful control factor. Additionally, a negative correlation was found between performance and the anger / frustration scale, consistent with previous research in toddlers that found those who performed better on an EF task were also more able to regulate their anger and

frustration (Gerardi-Caulton, 2000). Similarly, Carlson and Wang (2007) investigated the relations between individual differences in inhibitory control and emotion regulation in a sample of 4- to 6-year-old children. They found that performance on the Simon says task was positively associated with a task assessing emotional understanding, suggesting greater IC was related to greater emotional understanding. Further, the authors reported a negative association between inhibitory performance and the disappoint gift task, suggesting children with greater IC had better emotion regulation. Critically, the associations between inhibitory control and emotion regulation held even after controlling for age and verbal ability. In a related study, Kochanska et al. (1997) collected longitudinal data to examine the role of IC to the development of conscience in childhood. Specifically, children were assessed at toddler, pre-school, and early school age. The authors found several positive associations between IC performance and conscience measures such as initiating and sustaining mundane activity and suppressing a desired but prohibited behaviour. Further, children who scored higher on the battery of tasks measuring IC were also reported as more internalised, opening the possibility that early differences in IC forecast future personality development, especially in aspects of conscientiousness or constraint (Kochanska et al., 1997). Taken together, these finding suggest IC is an important contributor to children's socio-emotional development.

1.13.2 Role of the home environment

As described in section 1.7.2, the home environment is an umbrella term used to describe a set of variables relating to the environment a child is reared in. Thus, the home environment can include aspects of the child's physical environment, as well as social factors such as the quality of the parent-child relationship. For instance, Moilanen et al. (2010) conducted a longitudinal study on young children's IC between the ages of 2 and 4 and investigated whether demographic variables and parenting behaviours influenced inhibitory development. They found that higher levels of observed positive parenting at age 2 predicted children's IC growth between the ages of 2 and 4, suggesting

that supportive, positive parenting facilitates the development of inhibition in early childhood. These findings are in line with several previous studies that have also reported an association between supportive parenting and the development of self-regulation in childhood (Geeraerts et al., 2021; Kochanska & Aksan, 1995; Kopp, 1989). Children exposed to their parent's expectations of regulation may therefore have an increased awareness of their need to regulate (Laible & Thompson, 2007) and may learn self-regulatory strategies by imitating their parents (Forman & Kochanska, 2001). In a related study, Bosquet Enlow et al. (2019) examined the role of maternal and child lifetime stress, maternal caregiving in infancy and early childhood, and infant temperament on WM and IC. Maternal demographics were collected during pregnancy and infant temperament was assessed when children were 6-months old. When children were 3.5-years-old, they completed a go/no-go task assessing inhibition while mothers completed a questionnaire on exposure to stressors since pregnancy. The authors found poorer IC was associated with greater maternal lifetime exposure to stress / trauma during pregnancy, but not with maternal or child lifetime exposure to stress / trauma. Further, greater IC was associated with more emotionally supportive maternal behaviour during infancy and greater cognitive stimulation in childhood. Taken together, these findings suggest that positive and supporting parenting may be critical to the development of IC in childhood, and that factors which prevent supportive parenting (such as exposure to stress and trauma) consequently have a negative impact on inhibitory development.

SES is another environmental factor which has been extensively studied in the developmental literature due to its robust associations with cognitive development, including IC (Hassan et al., 2019; Sarsour et al., 2011; St. John, Finch, et al., 2019; St. John, Kibbe, et al., 2019; Xing et al., 2019). Specifically, Noble et al. (2005) compared performance between low SES and middle SES kindergartners on a number of EF tasks and found a significant group difference on a standard go/no-go task assessing IC. Further, when the authors examined the individual contributions of each SES factor to the variance in a composite of EF, they found that parental education accounted for 11.9% of the

variance, with no further contributions from parental occupation or income. This is in line with previous research that has suggested parental education might be the single most important factor of SES for predicting developmental outcomes (Bornstein et al., 2014). Interestingly however, Noble et al. (2005) also reported that SES did not statistically account for any variance over and above that predicted by language, suggesting SES might affect language development which in turn drives the developmental differences in EF. Differences in SES have also been associated with brain activity in regions important for inhibition. For instance, St. John, Finch, et al. (2019) recorded electrical activity in 4.5- to 5.5-year-old children while they performed a go/no-go task. They reported that higher household income was associated with a larger P3 amplitude (an index of inhibition and attention) in response to both go and no-go trials. The authors propose several reasons for this finding, as families on lower incomes may be exposed to more environmental toxins (Leventhal & Brooks-Gunn, 2001; Margolis et al., 2021), chronic stress (Hackman & Farah, 2009), poorer diets (Johnson & Markowitz, 2018), and engage in less quality parent-child interactions (Bradley & Corwyn, 2002), all of which have been negatively associated with cognitive development.

1.13.3 Role of the schooling environment

Inhibitory skills in the context of education have also received a fair amount of attention in the developmental literature, as school success is often defined not only in terms of learning capacity but by the ability to self-regulate (Bell et al., 2007). In a school setting, children are expected to exert control over their own behaviour, thoughts, and actions, drawing heavily on IC abilities. Children who are able to do so are at a clear advantage both in the classroom and on the playground (Bell et al., 2007). As discussed in section 1.7.3, researchers have come up with several ways to try measure the impact of schooling. The most effective of these methods is the school cut-off design, a quasi-experimental technique that relies on the fact that school districts determine eligibility for school enrolment based on an arbitrary cut-off date. While early research using this method focused on learned skills such as numeracy (Bisanz et al., 1995;

Christian et al., 2000) and literacy (Morrison et al., 1995; Varnhagen et al., 1994), recent years have seen an increase in research investigating how schooling may impact aspects of EF. For instance, Kim and colleagues (2021) compared performance on an IC task between first grade children and kindergarten children. Specifically, these researchers adopted a 2-month window, comparing children born 2 months prior to and 2 months after the school cut-off date. Interestingly, they found the kindergarteners showed greater improvements than the first-grade children across the year. However, this result should be interpreted with caution. Based on the data presented, it appears the first-grade children may have been significantly older than the kindergartners at baseline, which was not controlled for in the analyses. Second, initial differences existed between the two groups at the start of the year, with the first graders outperforming the kindergarteners at baseline. Hence, it is unclear whether the kindergarteners improved more from the experience of kindergarten or were just "catching up" in performance with age. Contrary to these findings, Brod et al. (2017) conducted the first and only neuroscientific investigation into schooling-related effects on IC and found no differences in go/no-go task performance between kindergarten and first-grade children. However, the authors did report greater activation in the right superior PPC, an area associated with sustained attention, for correct go trials in the children who had attended school. Thus, the authors concluded the increased engagement of the PPC may reflect a direct effect of the schooling experience, where children are required to sit still and pay attention for extended periods of time.

1.14   Summary

IC is a core component of EF involved in controlling one's thoughts, behaviours, attention, and emotions in order to inhibit a dominant response in favour of a more necessary or appropriate one. Several tasks have been developed to measure IC across development, with some researchers making the distinction between "simple" (low WM demand) and "complex" (high WM demand) tasks. Converging evidence suggests rapid behavioural improvements in response

inhibition occurs between the ages of 2 and 5 (see Garon et al. (2008) for a review), with more gradual refinements in accuracy and efficiency occurring across middle to late childhood (Best & Miller, 2010). Findings from the neurodevelopmental literature suggest global, more diffuse brain activation in early and middle childhood. With development, this pattern of activation becomes more efficient and localised to specific areas in the PFC and parietal lobe. Several key factors which contribute to individual differences in IC development between the ages of 4 and 6 have been discussed, including child characteristics, home environment and parental factors, as well as the schooling environment. Chapter 4 (section 4.2) provides further details on the nature of these individual differences and highlights some contradictory findings in the literature. Specifically, Chapter 4 seeks to explain these contradictory findings and determine whether further insight into the neural pathways underlying response inhibition in pre-schoolers could be gained by examining performance differences, and to relate these differences to temperamental and environmental factors. Lastly, Chapter 5 (section 5.2) provides a detailed review of the literature on schooling-related effects on two types of IC, namely response inhibition and response monitoring and identifies research questions that warrant further investigation. Using the school-cut off design, Chapter 5 will establish whether entering formal schooling leads to increased engagements of the neural networks underlying response inhibition and response monitoring and determine whether improvements in these two domains predicts academic success.

1.15   Thesis outline

Key Research Questions:

What are the key factors which contribute to individual differences in EF and its neural correlates in 4.5-year-old children? Can we isolate the unique contributions of schooling on EF and its neural correlates in 4- to 6-year-old children? To what extent do schooling-related changes in behaviour and/or brain activation underlying EF predict academic outcomes over time in 4- to 6-year-old children?

To answer these key questions, the research was conducted and reported in the following chapters:

Chapter 2. HOME ASSESSMENT OF VISUAL WORKING MEMORY IN PRE-SCHOOLERS REVEALS ASSOCIATIONS BETWEEN BEHAVIOUR, BRAIN ACTIVATION AND PARENT REPORTS OF LIFE STRESS. This chapter investigates individual differences in behaviour and brain activation underlying VWM in pre-schoolers and relates these differences to parent-reported measures of the child's environment and temperament. A portable fNIRS system was used to record from the frontal and parietal cortices of 4.5-year-old children ($N = 74$) while they completed a colour change-detection task in their homes. Parents were asked to fill in questionnaires assessing factors such as child temperament and the quality of the home environment.

Chapter 3. DISENTANGLING AGE AND SCHOOLING EFFECTS ON VISUAL WORKING MEMORY DEVELOPMENT: AN fNIRS INVESTIGATION. This chapter investigates whether the first year of formal schooling results in an improvement in VWM performance and underlying changes in brain activation and determine whether this can predict academic outcomes across time. Behavioral and fNIRS brain activation data in response to a colour change-detection task as well as measures of academic achievement were collected on two groups of children in their homes across two years. At the first data collection timepoint, children were 4.5 years old and neither group had started

school. At the second data collection timepoint, one group (P1, N = 39) had completed one full year of schooling while the other group had stayed in kindergarten (KG, N = 40).

Chapter 4. NEURAL NETWORK UNDERLYING RESPONSE INHIBITION IN PRE-SCHOOLERS VARIES ACCORDING TO PERFORMANCE. This chapter investigates individual differences in behaviour and brain activation underlying IC in pre-schoolers and relates these differences to parent-reported measures of the child's environment and temperament. A portable fNIRS system was used to record from the frontal and parietal cortices of 4.5-year-old children (N = 66) while they completed a go/no-go task in their homes. Parents were asked to fill in questionnaires assessing child temperament and the quality of the home environment.

Chapter 5. DISENTANGLING AGE AND SCHOOLING EFFECTS ON INHIBITORY CONTROL DEVELOPMENT: AN fNIRS INVESTIGATION. This chapter examines whether the longitudinal development of two types of IC (response inhibition and response monitoring) and underlying brain function differs by schooling experience, and whether this can predict academic outcomes across time. Behavioral and fNIRS brain activation data in response to a go/no-go task as well as measures of academic achievement were collected on two groups of children in their homes across two years. At the first data collection timepoint, children were 4.5 years old and neither group had started school. At the second data collection timepoint, one group (P1, N = 40) had completed one full year of schooling while the other group had stayed in kindergarten (KG, N = 40).

CHAPTER 2 HOME ASSESSMENT OF VISUAL WORKING MEMORY IN
PRE-SCHOOLERS REVEALS ASSOCIATIONS BETWEEN BEHAVIOUR,
BRAIN ACTIVATION AND PARENT REPORTS OF LIFE STRESS

Courtney A. McKay, Yee Lee Shing, Eva Rafetseder, Sobanawartiny
Wijeakumar

2.1 Abstract

VWM is reliably predictive of fluid intelligence and academic achievements. The
objective of the current study was to investigate individual differences in pre-
schoolers' VWM processing by examining the association between behaviour,
brain function and parent-reported measures related to the child's environment.
We used a portable fNIRS system to record from the frontal and parietal
cortices of 4.5-year-old children (N = 74) as they completed a colour change-
detection VWM task in their homes. Parents were asked to fill in questionnaires
on temperament, academic aspirations, home environment and life stress.
Children were median-split into a LP and a HP group based on the number of
items they could successfully remember during the task. LPs increasingly
activated channels in the left frontal and bilateral parietal cortices with
increasing load, whereas HPs showed no difference in activation. Our findings
suggest that LPs recruited more neural resources than HPs when their VWM
capacity was challenged. We employed mediation analyses to examine the
association between the difference in activation between the highest and lowest
loads and variables from the questionnaires. The difference in activation
between loads in the left parietal cortex partially mediated the association
between parent-reported stressful life events and VWM performance. Critically,
our findings show that the association between VWM capacity, left parietal
activation and indicators of life stress is important to understand the nature of
individual differences in VWM in pre-school children.

2.2 Introduction

VWM is a short-term storage system responsible for detecting changes in the world as they occur. VWM capacity is reliably predictive of cognitive functions (Fukuda et al., 2010) and a host of academic skills (Alloway & Alloway, 2010; R. Bull & Scerif, 2001; Gathercole, Pickering, Knight, et al., 2004; Swanson & Beebe-Frankenberger, 2004). Critically, it accounts for around 40% of individual differences in global fluid intelligence (Fukuda et al., 2010), and for up to 46% of individual differences in performance on a cognitive battery of tasks (M. K. Johnson et al., 2013).

A common task for assessing VWM is the change-detection task (Luck & Vogel, 1997), where subjects are consecutively presented two arrays of items and asked to identify if the items were identical across both arrays. This task is particularly well-suited for examining human development, as age-related changes in capacity can be captured by varying the number of presented items. Using this task, Simmering (2012) found that three-year-olds had a capacity of 1.5 to 2 items. Capacity increased to 2 to 3 items by five years of age. This finding was confirmed by Buss and colleagues (2014), who found that three-year-old children had a capacity of 1.2 items while four-year-old children had a capacity of 1.8 items when attending to a shape change-detection task.

Consistent behavioural findings from manipulating VWM load have been accompanied by the involvement of a distributed brain network in adults. VWM capacity is associated with activity in the posterior parietal and superior occipital cortices, with activation increasing as the number of items in the array increases, and reaching a plateau at maximum capacity (Todd & Marois, 2004). Activity in the posterior parietal cortex has also been shown to predict individual differences in capacity in adults (Todd & Marois, 2005). Further, load-dependent responses have been found in the right intra-parietal sulcus and the right superior intraparietal sulcus (Ambrose et al., 2016). Koenigs and colleagues (2009) assessed a wide range of memory functions in patients with lesions in either hemisphere of the superior parietal cortex and found that this area was directly involved in the manipulation and re-arrangement of information for both auditory-verbal and visuospatial stimuli. Separately, another body of research has shown

that the prefrontal cortex is responsible for maintaining and encoding representations of task-relevant information into WM (A. Baddeley, 2003; Miller & Cohen, 2001). More recently, Christophel and colleagues (2017) proposed that WM relies on the interplay between sensory regions in the posterior cortex that retain low-level features and frontal regions that retain more abstract stimuli that are gradually transformed to an appropriate behavioural response. Taken together, these findings suggest that WM emerges from a coordinated system involving a distributed network of brain regions across the posterior and anterior cortices.

While fMRI studies have provided valuable insights into the neural processes underlying VWM in adults, there are limitations in its application in early development. fMRI scanners are noisy, and participants are required to lie still, an obstacle for young children. More recently, early developmental work has employed an alternative technique - functional near-infrared spectroscopy (fNIRS). fNIRS systems shine near-infrared light (ranging from 650nm-1000nm) through the head to detect changes in oxygenated haemoglobin [HbO] and deo-oxygenated haemoglobin [HbR] (Boas et al., 2014). fNIRS has been reliably used across the lifespan to study changes in activation in the frontal and parietal networks underlying VWM (Buss et al., 2014; Sato et al., 2013; Tsujimoto et al., 2004; Wijeakumar et al., 2019; Wijeakumar, Huppert, et al., 2017; Wijeakumar, Magnotta, et al., 2017). Using fNIRS, Tsujimoto and colleagues (2004) examined VWM performance on a change-detection task in a sample of adults and five-year-old children. They found that activity in the bilateral areas of the prefrontal cortex was similar in both groups, characterised by an increase in HbO with the onset of the memory array. These results demonstrated for the first time that the left prefrontal cortex is also involved in VWM processing in pre-schoolers. An fNIRS study examining VWM using a shape change-detection task in three- and four-year-old children found more robust activation in the parietal cortex in four-year-olds relative to three-year-olds (Buss et al., 2014). However, in contrast to what has been consistently found in the adult literature, the hemodynamic response did not plateau at maximum capacity – suggesting this neural effect may develop only after four years of age. Wijeakumar and colleagues used a

portable fNIRS system to investigate the neural networks underlying VWM processing in infants and children in rural India. They found that VWM performance was inversely correlated with activation in the bilateral frontal cortices, such that increased activation in this area was associated with poorer VWM performance (Wijeakumar et al., 2019). This study highlights another crucial advantage of fNIRS over other neuroimaging modalities - its portability, allowing researchers to freely explore cognitive processes outside of a traditional lab setting.

Individual differences in the development of VWM are predictive of subsequent academic achievements such as math abilities (Bull, Espy, & Wiebe, 2008) and reading comprehension (Swanson & Berninger, 1996). These individual differences might stem from exposure to specific parental and home environmental factors. Fishbein and colleagues showed that cognitive function in children was associated with certain home child-rearing conditions (Fishbein et al., 2019). Specifically, positive aspects of the home environment predicted better performance on two tasks assessing visual information processing and WM. Parental/home measures might also be associated with brain structure and brain function. Higher family income has been linked to greater white matter integrity in cortical and subcortical brain areas (Noble et al., 2015; Ursache et al., 2016). Early childhood deprivation is also associated with prefrontal cortical volume and surface area (Mackes et al., 2020). In rural settings in India, weaker activation in parts of the frontal cortex in response to a preferential looking VWM task in children was linked to poorer maternal education and income (Wijeakumar et al., 2019). It is possible that such associations between a specific brain structure or function and parent/home measures could inform effects on behavioural performance and/or other cognitive functions subserved by the same areas in later development. However, the nature of trivariate associations between behavioural performance, brain function and parental and home environment measures are not well-understood. In the current study, we probe this association by investigating how individual differences in VWM performance and underlying brain function are related to parental and home environment factors. We recruited a specific group of pre-schoolers with little variation in age to investigate

individual differences during the critical period before children begin formal education. The present study capitalised on the portability of the fNIRS system and, to the best of our knowledge, is the first to examine individual differences in VWM processing using home-based testing. Laboratory testing allows for experiments to be conducted under strictly controlled conditions. However, in doing so, children are tested in an artificial and stressful environment. By conducting all testing in a home environment, we hope to provide children with the opportunity to perform the task in a relaxed environment and increase the ecological validity of the paradigm.

Based on findings by Simmering (2012), we hypothesized that overall, VWM performance would decrease as load increases. Our predictions of brain activation patterns in low and high-performing children are informed by contrasting accounts from previous findings. First, in general, challenging task demands through increasing VWM load elicits increasing brain activation in adults until capacity limit is severely strained (Linden et al., 2003; Rypma & D'Esposito, 1999; Todd & Marois, 2004, 2005). Second, along the same vein, Jaeggi et al. (2007) showed that low-performing adults elicited greater load-dependent activation than high-performing adults in parts of the frontal cortex. Here, the authors argued that low-performers might recruit additional attentional and strategy-related mechanisms during difficult conditions that might even be detrimental to their performance, whereas, high-performers were able to demonstrate efficient processing, stabilize their resources and improve performance. Third, in contrast to these two previous set of findings, Buss et al. (2014) showed that four-year-old children showed better performance and greater activation in the parietal cortex compared to three-year-old children suggesting that behavioural gains were associated with greater, and not lesser activation. However, Buss and colleagues investigated *developmental* changes and not *performance-related* changes, affording the question whether with a larger sample of four-year-old children and testing performance differences, they might have observed similar findings to that of Jaeggi et al. (2007). Further, they did not formally test the association between behavioural performance and brain activation. Lastly, Wijeakumar and colleagues found that

greater activation in parts of the frontal cortex was associated with poorer VWM performance in a preferential looking task where a changing and non-changing flashing display of items were presented side by side (Wijeakumar et al., 2019). They suggested that the inability to suppress distraction from the non-changing side elicited greater activation in children with poor VWM performance. Taking these accounts into consideration, we predicted that low-performing children from our sample would require greater cognitive effort to meet the challenging VWM loads of the task, and as a result, would elicit more activation than high-performing children

2.3 Methods

2.3.1 Participants

Ninety-five 4.5-year-olds (45 females, M_{age} = 53.5 months, *SD* = 1.2) participated in the study. Additionally, one of the parents of each child also took part in the study by filling out a series of questionnaires. We recruited participants by contacting gateway organizations such as nurseries and leisure centres and providing them with our study information. Parents of eligible children got in touch with us via our website, email, or over the phone to schedule a testing session. Data were collected on participants in their homes across Scotland. Children received a small honorarium and gift for participation. All participants had normal or corrected to normal vision, no history of colour-blindness, no neurological conditions, and all mothers experienced a full-term pregnancy (37 to 42 weeks) with an uncomplicated birth. Parents gave written informed consent and children gave verbal assent prior to testing. The research was approved by the General University Ethics Panel (GUEP 375 – see Appendix A) at the University of Stirling.

Data from twenty-one children had to be excluded from analyses; five children refused to participate in the task, twelve children interfered with the neuroimaging set-up (pulled the cap off) before the completion of the task, two children had thick hair that prevented contact between the optodes and the scalp and caused poor singla quality, and data from two children was lost due to

experimenter error. A total of 74 children (37 females, M_{age} = 53.5 months, *SD* = 1.3) contributed to the final analyses.

2.3.2 Experimental task

The colour change-detection task (Simmering, 2012) was used to measure VWM performance in children. The task was explained using 3 × 3 inch flashcards with coloured squares, to ensure children understood the rules. The experimenter placed the first card (with one coloured square) on the table for approximately 2 s and asked the child to remember the card. Then, the experimenter turned over the first card and placed a second card (with one square of the same or different colour) on top. The child was asked if the two cards were the same or different. Once the child responded, the experimenter turned over both cards and praised the child if they had correctly answered the question and corrected them if they had given the wrong answer. This practice session was repeated with flashcards containing two and then, three coloured squares. The flashcards were displayed again if the child made a mistake. Once the child had correctly answered all the practice trials, the experimental task was run in E-prime V.3 software on an HP laptop with a 14-inch screen. The computer task began with three practice trials, the first trial had one square, the second trial had two squares and the third trial had three squares. Children were corrected if they made a mistake before commencing the experimental trials. Each trial of the experimental task began with a memory array of coloured squares presented for 2 s, followed by a delay of 1 s, and finally, by the test array of coloured squares (see Figure 1). The test array remained on the screen until a response was made. During 'same' trials, the colours in both arrays were identical. During 'different' trials, the colour of one square in the test array was different from the otherwise identical memory array. At the end of each trial, the experimenter asked the child if the two cards were the same or different. Children gave a verbal response, which the experimenter recorded on the laptop. An inter-trial interval of 1 s (50% of the trials), 3 s (25% of the trials) or 5 s (25% of the trials) was used at the end of

each trial. During every trial, the memory and test arrays were presented one after another, occupying the same position on the screen. Across trials, arrays were presented on alternating sides of the screen to avoid confusion in children who tried to compare the test array in trial 1 with the sample array in trial 2. VWM load was manipulated from 1 to 3 square items (load 1, load 2 and load 3). Each load was presented in a block consisting of randomized presentations of eight same and eight different trials.
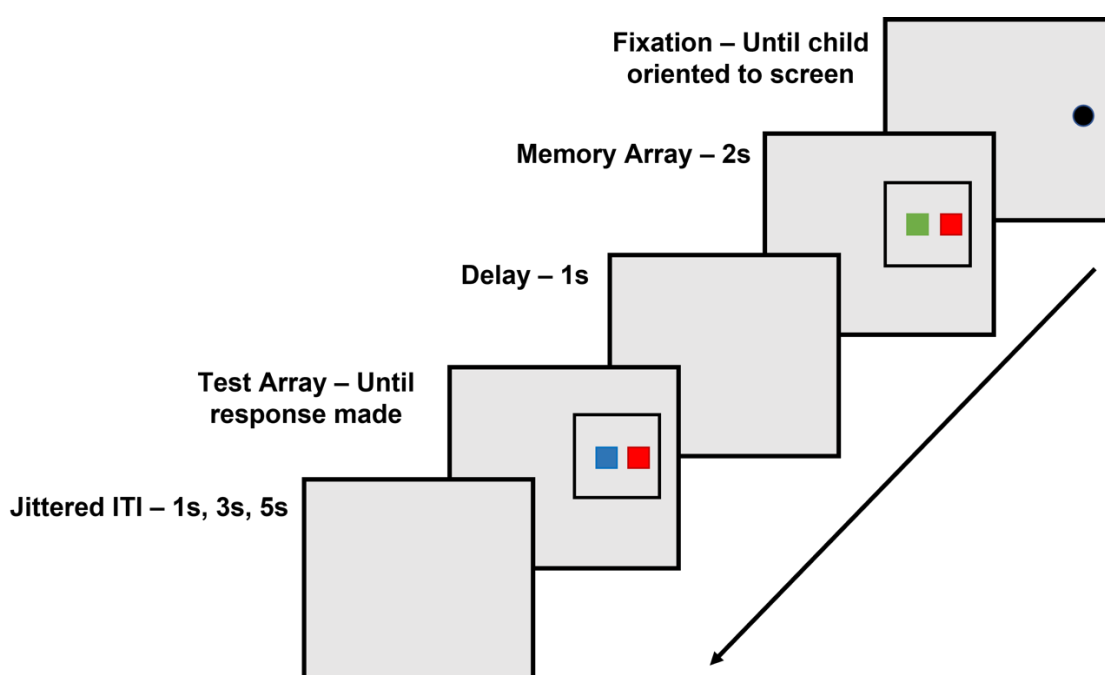
Figure 1. Colour change-detection task – Load 2 different trial.

2.3.3 fNIRS data acquisition

fNIRS data were collected at 7.81 Hz using a NIRSport system 8 × 8 (8 sources 8 detectors)/release 2.01 with wavelengths of 850 and 760 nm. Fibre optic cables carried light from the machine to a NIRS cap. Probe geometry was designed by collating regions of interest (ROI) from previous fMRI VWM literature (Wijeakumar et al., 2015). Probe geometry consisted of four channels each on the left and right frontal cortices, and three channels each on the left and right parietal cortices (see Figure 2). Note that short-source-detector

channels were not used to regress scalp haemodynamics as all the channels were directed toward maximizing coverage of the frontal and parietal cortices. Four cap sizes (50, 52, 54, and 56 cm) were used to accommodate different head sizes. Source-detector separation was scaled according to cap size (50 cm cap: 2.5 cm; 52 cm cap: 2.6 cm; 54 cm cap: 2.7 cm and 56 cm cap: 2.8 cm). To synchronize behavioural and fNIRS data, a McDaq data acquisition device (www.mccdaq.com) was used to send information from the task presentation laptop to the fNIRS system. The trigger was sent at the start of the memory array in each trial.
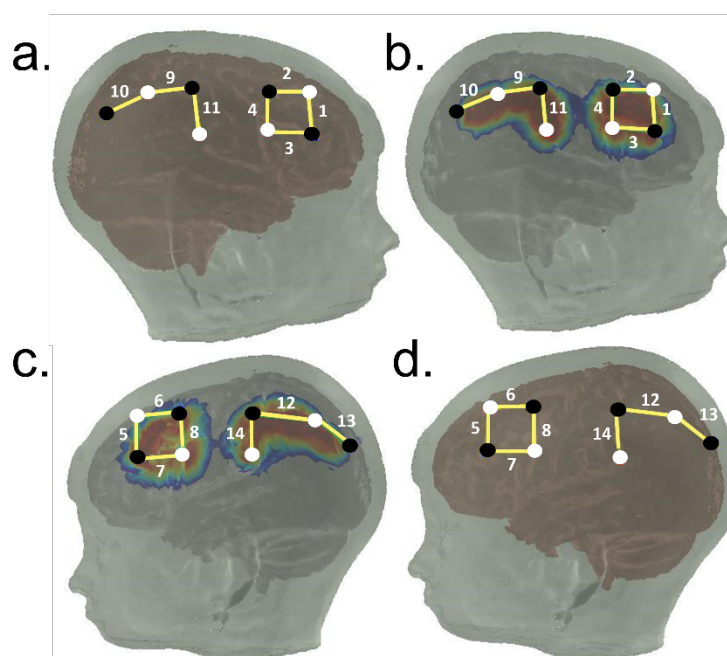
Figure 2. (a) and (d) Probe geometry over the right and left hemispheres. The white circles represent the sources and the black circles represent the detectors. **(b) and (c)** Sensitivity profiles after running Monte Carlo Simulations with 100 million photons.

2.3.4 Procedure

We collected data from children in their homes which allowed us to move away from a traditional lab setting. Two researchers were present during each

session. One researcher was responsible for checking the quality of the fNIRS signals, while the other researcher attended to the child and parent. We requested all children to sit on a chair at a table to make sure that all the equipment could be safely set up. The head circumference of the child was measured so that the researchers could select the appropriately sized fNIRS cap. Once the cap was fitted to the child's head, measurements were taken from the inion to the nasion and from the two peri-auricular points to make sure that the cap was centred. Children were given an iPad to watch cartoons during the set-up process. Once the set- up was complete (approx. 15 min, see Figure 3), the experimenter began the session by introducing the task as "the colour game" and explained the rules using the flashcards. Children were then told that they were going to play the same game on the computer. Children were rewarded with one sticker after they completed all the trials in each load regardless of their performance (correct or incorrect) to maintain their motivation.

Figure 3. Experimental set-up inside a participant's home. **(a)** Beginning of set-up **(b)** 10 minutes into set-up **(c)** Complete set-up after 15 minutes.

2.3.5 Parental questionnaires

Parents were given a booklet of questionnaires to complete. Variables from these questionnaires have previously been shown to be associated with cognitive function in children. The Strengths and Difficulties Questionnaire (Goodman, 1997) assesses children's behavioural and emotional characteristics. This questionnaire has been used to investigate individual differences in pre-

schoolers EF (Dias et al., 2017; Hughes et al., 1998, 2000; Sulik et al., 2015). The Parenting Daily Hassles scale (Crnic & Booth, 1991; Crnic & Greenberg, 1990) assesses the frequency and impact of events that routinely occur in families with young children. Previous work has shown a negative association between frequent daily hassles and children's cognitive ability (Stuart, 2005). The Confusion, Order and Hubbub Scale (Matheny et al., 1995) measures the amount of noise, confusion and disorganisation present in the home. Twin studies have found that chaos in the home is an independent predictor of cognitive outcomes (S. A. Hart et al., 2007; Petrill et al., 2004). The Parenting Stress Index (Abidin et al., 2013) assesses the degree of stress in the parent-child relationship. Two previous studies found that parenting stress predicted lower cognitive scores in children (de Cock et al., 2017; Harewood et al., 2017). Lastly, a socio-economic scale that assessed income, education and parental aspirations was also included. Several studies have shown a strong association between socio-economic status and children's cognitive ability and achievement (Ardila et al., 2005; Duncan et al., 2011; Hackman et al., 2014, 2015; Hackman & Farah, 2009; Noble et al., 2012; Wijeakumar et al., 2019). For a detailed list of subscores, see Appendix B, Table B1.

2.3.6 Behavioural analyses

Accuracy (A') and capacity (K) was calculated from hits (H) and false alarms (FA) based on the behavioural responses. A' was calculated using Grier's (1971) formula, updated by Aaronson and Watts (1987), where A' = 1 indicates perfect performances, and A' = 0.5 indicates chance performance. The following formula is calculated to account for a "yes" bias.

If H ≥ FA: A' = ½ + { [(H - FA) * (1 + H - FA)] / [4 * H * (1 − FA)] }

If H < FA: A' = ½ - { [(FA - H) * (1 + FA - H)] / [4 * FA * (1 − H)] }

As demonstrated in Simmering (2016), for the cases where H and FA were equal to each other, accuracy was set to 0.5. A' represents how accurately individuals perform at each load in the task.

K was calculated for each load using Pashler's (1988) formula:

K = Load * (H – FA) / (1 – FA)

K represents the number of items that are successfully stored in WM. Note that, at most, K can equal the maximum number of items as the presented load. Maximum K was estimated as the highest K value across all loads. Thus, maximum K can, at most, equal the highest load. We ran a repeated-measures ANOVA with a within-subjects factor of load to investigate how A' changed as a function of load. We also applied median-splitting on maximum K estimates to divide our sample into low-performers (LPs) and high-performers (HPs). We relied on maximum K for this categorization as the number of items stored is the most important measure of VWM performance.

2.3.7 Pre-processing fNIRS signals

fNIRS data were pre-processed using the Homer2 package (https://www.nitrc.org/projects/homer2/). Raw data were pruned using the *enPrunechannels* function (dRange = 0.01–300, SNRthresh = 2, SDrange = 0–45). Signals were converted from intensity values to optical density (OD) units using the *Intensity2OD* function. Data were corrected for motion using the *hmrMotionCorrectPCArecurse* func- tion (tMotion = 1, tMask = 1, STDEVthresh = 50, AMPthresh = 0.5, nSV = 0.97, maxIter = 5, turnon = 1). Data were scanned for motion artifacts using *hmrMotionArtifactByChannel* function (tMotion = 1, tMask = 1, STDEVthresh = 50, AMPthresh = 0.5). Then, the function *enStimRejection* (tRange = −1 to 10) was used to turn off stimulus triggers during any segments that contained motion artifacts. The data were band-pass filtered using *hmrBandpassFilt* to include frequencies between 0.016 Hz and 0.5 Hz. Using the function hmrOD2Conc, the OD units were converted to concentration units (partial pathlength factor = 6 for each wavelength). Lastly, the function *hmrBlockAvg* was used to calculate the block average for a time window of −1 to 12 s. The mean activation from −1 to 0 s was used as the baseline to subtract from activation in the rest of the window (as specified in function *hmrBlockAvg*).

2.3.8 fNIRS group analyses

Only correct trials were included in the fNIRS group analyses. We chose a haemodynamic response window from the 3rd to 6th second for further analyses. This time window was selected based on findings from Buss et al. (2014) and on our observations of the peak of the haemodynamic response of the task. Note that we do not consider a 'later' window (after the 6th second) as trials with shorter inter-trial intervals would also include signals elicited by succeeding trials.

We computed the mean haemodynamic activation for the chosen window for each load (1, 2, 3), trial type (same, different), chromophore (HbO, HbR), channel (1 to 14) and participant ($N = 74$). Note that the mean number of correct trials included for HPs were 15 ± 0.17 trials for load 1, 14 ± 0.34 trials for load 2 and 12 ± 0.32 trials for load 3. The mean number of correct trials included for LPs were 15 ± 0.24 trials for load 1, 12 ± 0.43 trials for load 2 and 10 ± 0.27 trials for load 3.

A repeated measures ANOVA was run for each of the 14 channels. Each ANOVA included within-subject factors of load (1, 2 and 3 items), trial type (same and different) and chromophore (HbO, HbR) and a between-subjects factor of group (HPs and LPs). We only focused on effects that showed a significant interaction with chromophore to maximize the possibility of observing differences between HbO and HbR activation.[1] We examined channels with a significant interaction between load and chromophore to assess if activation increased with increasing load as shown in previous studies. Next, we examined channels that showed a significant interaction between group, load and chromophore to examine differences between LPs and HPs. The Benjamini-Hochberg test was run with a false discovery rate of 0.05 to control for the number of channels that were included in the analyses. Here, individual *p*-values from interaction between group, load and chromophore for each channel were ranked in ascending order, with 1 being the smallest *p*-value, two

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[1] Typically, the concertation of HbO is expected to rise after brain activation due to higher blood flow, while HbR is washed out and is expected to decrease. Thus, focusing on regions in the brain which show a difference between HbO and HbR can increase the validity of the fNIRS signal.

being the second smallest value and so forth. We then calculated each individual p-value's critical Benjamini-Hochberg value using the following formula: (i/m)Q, where, i = individual p-value rank, m = total number of tests, and Q = false discovery rate of 0.05. Finally, we compared our original p-values to the critical Benjamini-Hochberg value to find p-values that were smaller than the critical value. All channels with p-values for the interactions between group, load and chromophore below this highest p-value were considered significant. Lastly, Bonferroni correction was applied to the post-hoc tests conducted in following up these significant interactions.

2.3.9 Correlations between behaviour, brain function, and parental questionnaires

The questionnaire data were log-transformed to account for skewed distributions. All data (questionnaires, behaviour and brain function) was screened for outliers that were 3 standard deviations above or below the mean. We identified nine outliers - one in the right parietal cortex, one in the left parietal cortex, three in the Strengths and Difficulties Questionnaire, one in the Parenting Daily Hassles Scale, two in the parental aspirations measure and one in the parental education measure. Next, we winsorized these outliers by replacing their values with the observation closest to them but are just below the threshold for defining outliers. Then we correlated our questionnaire variables with our behavioural and brain measures. The Benjamini-Hochberg test run with a false discovery rate of 0.1 was able to control for the number of significance tests on correlations that we performed. All correlations with p-values below the critical p-value were considered significant.

2.4 Results

2.4.1 Behavioural results

The repeated measures ANOVA on A' revealed that the main effect of load was significant ($F[2, 146] = 90.37$, p <.001, partial eta square (η_p^2) = 0.301). Follow-

up pairwise comparisons revealed that accuracy at load 1 (M = 0.96, SD = 0.04) was greater than at load 2 (M = 0.86, SD = 0.17, $t[73]$ = 5.29, p <0.001), and load 3 (M = 0.82, SD = 0.13, $t[73]$ = 9.5, p <0.001). Furthermore, accuracy at load 2 was greater than accuracy at load 3, ($t[73]$ = 2.27, p = 0.026) – see Figure 4a. These results were in agreement with previous findings (Simmering, 2012).

Median-splitting was applied to the maximum K estimates. The median maximum K was 2 items, with 13 children performing at the median. We decided to include these 13 children into the HP group because their individual accuracy scores at load 3 fell above the median accuracy. This resulted in a total of 39 HPs and 35 LPs. Figure 4b shows the mean maximum K estimates for HPs (2.4 ± 0.06 items) and LPs (1.5 ± 0.06 items).
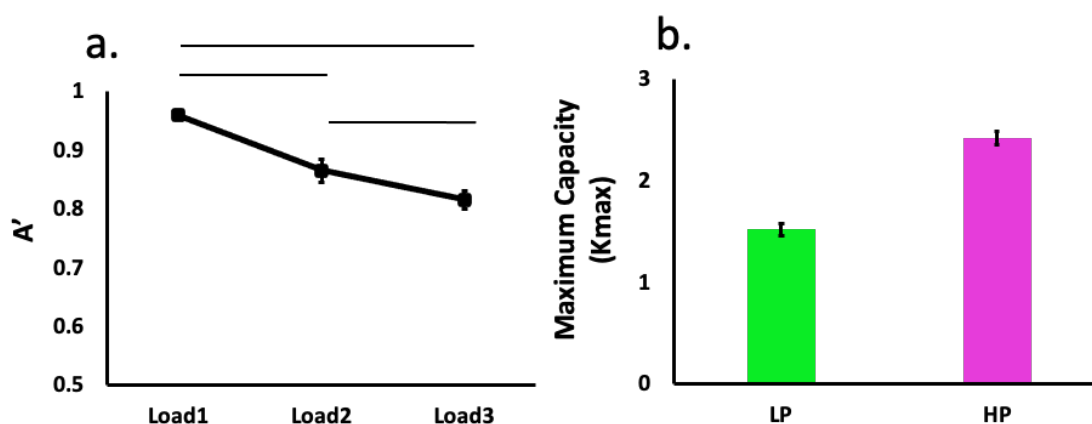
Figure 4. (a) A' decreased as load increased from 1 to 3 items. **(b)** Maximum K estimates for high and low performers. Error bars show SEM. '-' indicates significance at p<.05.

2.4.2 fNIRS results

Channels showing significant interactions between load and chromophore and group, load and chromophore are shown in Table 1. Posthoc results are shown for HbO activation. See Appendix C, Table C1 for the posthoc results for HbR

activation. Note that only effects in channels that survived the Benjamini-Hochberg correction are reported. The interaction between load and chromophore was significant in channels overlying the left middle frontal gyrus (F[2,144] = 8.599, p = 0.000; F[2,144] = 4.857, p = 0.009) and left inferior frontal gyrus (F[2,144] = 7.542, p = 0.001). Posthoc tests revealed that activation at load 3 was greater than activation at load 1 and load 2. Figure 5 shows the change in HbO activation with load for channel 6 overlying the left middle frontal gyrus.

A significant interaction between group, load and chromophore was observed in channels overlying the left middle frontal gyrus (F[2,144] = 4.773, p = 0.01 – Figure 6a,c,e), left inferior frontal gyrus (F[2,144] = 4.616, p = 0.011 – Figure 6b,d,f), right angular gyrus (F[2,144] = 6.604, p = 0.002 – Figure 7a,c,e), right supramarginal gyrus (F[2,144] = 6.005, p = 0.003 – Figure 7b,d,f), left inferior parietal lobule (F[2,144] = 4.843, p = 0.009 – Figure 8a,c,e) and left supramarginal gyrus (F[2,144] = 4.646, p = 0.011 – Figure 8b,d,f). Across all these areas, LPs showed greater activation at load 3 than at load 1. Importantly, HPs did not demonstrate this modulation of activation with increasing load. HPs showed greater activation than LPs at load 1 in channels overlying the left middle gyrus, left inferior frontal gyrus, right angular gyrus, right supramarginal gyrus and left supramarginal gyrus. Finally, LPs showed greater activation than HPs at load 3 in a channel overlying the left middle frontal gyrus.

Table 1. Channels showing significant interactions between load and chromophore and group, load and chromophore. Posthoc results are shown for HbO activation.

Channel No.	Brain Area (MNI coordinates)	Load x Chromophore (HbO)	Group x Load x Chromophore (HbO)
Channel 1	Right middle frontal gyrus		
Channel 2	Right middle frontal gyrus		
Channel 3	Right inferior frontal gyrus		
Channel 4	Right inferior frontal gyrus		
Channel 5	Left middle frontal gyrus	Load 3 > Load 1 ($p = 0.001$) Load 3 > Load 2 ($p = 0.002$)	
Channel 6	Left middle frontal gyrus	Load 3 > Load 1 ($p = 0.011$)	Load 3: LPs > HPs ($p = 0.037$) LPs: Load 3 > Load 1 ($p < 0.001$) Load 1: HPs > LPs ($p = 0.024$)
Channel 7	Left inferior frontal gyrus	Load 3 > Load 1 ($p = 0.01$)	
Channel 8	Left inferior frontal gyrus		LPs: Load 3 > Load 1 ($p = 0.004$) LPs: Load 2 > Load 1 ($p = 0.045$) Load 1: HPs > LPs ($p = 0.016$)
Channel 9	Right angular gyrus		LPs: Load 3 > Load 1 ($p = 0.004$) Load 1: HPs > LPs ($p = 0.001$)
Channel 10	Right superior occipital gyrus		
Channel 11	Right supramarginal gyrus		LPs: Load 3 > Load 1 ($p = 0.011$) Load 1: HPs > LPs ($p = 0.025$)
Channel 12	Left inferior parietal lobule		LPs: Load 3 > Load 1 ($p = 0.009$)
Channel 13	Left angular gyrus		
Channel 14	Left supramarginal gyrus		LPs: Load 3 > Load 1 ($p = 0.033$) Load 1: HPs > LPs ($p = 0.01$) Load 2: HPs > LPs ($p = 0.036$)
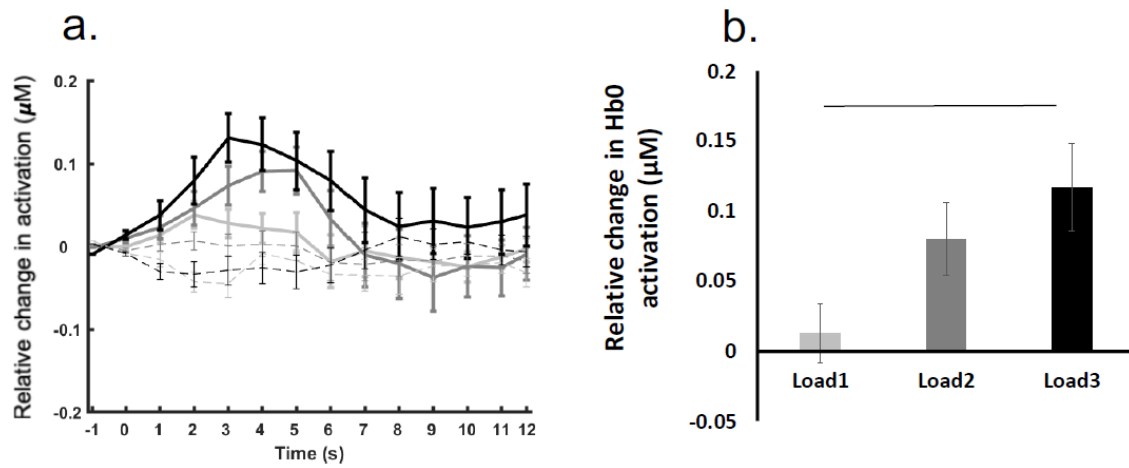
Figure 5. (a) HbO (solid lines) and HbR (dashed lines) activation in channel 6 overlying the left middle frontal gyrus. Load 1 is shown in light grey, load 2 in dark grey, and load 3 in black. Error bars show 1 SE averaged over 1sec intervals. **(b)** Bar plot showing greater HbO activation at load 3 compared to load 1. Error bars show SEM. '-' indicates significance at $p<.05$.

a. Mean HbO activation in Channel 6

b. Mean HbO activation in Channel 8

c. Activation in Channel 6 in HPs

d. Activation in Channel 8 in HPs

e. Activation in Channel 6 in LPs

f. Activation in Channel 8 in LPs

Relative change in activation (μM)

HbO HPs Load 1   HbO HPs Load 2   HbO HPs Load 3
HbR HPs Load 1   HbR HPs Load 2   HbR HPs Load 3
HbO LPs Load 1   HbO LPs Load 2   HbO LPs Load 3
HbR LPs Load 1   HbR LPs Load 2   HbR LPs Load 3
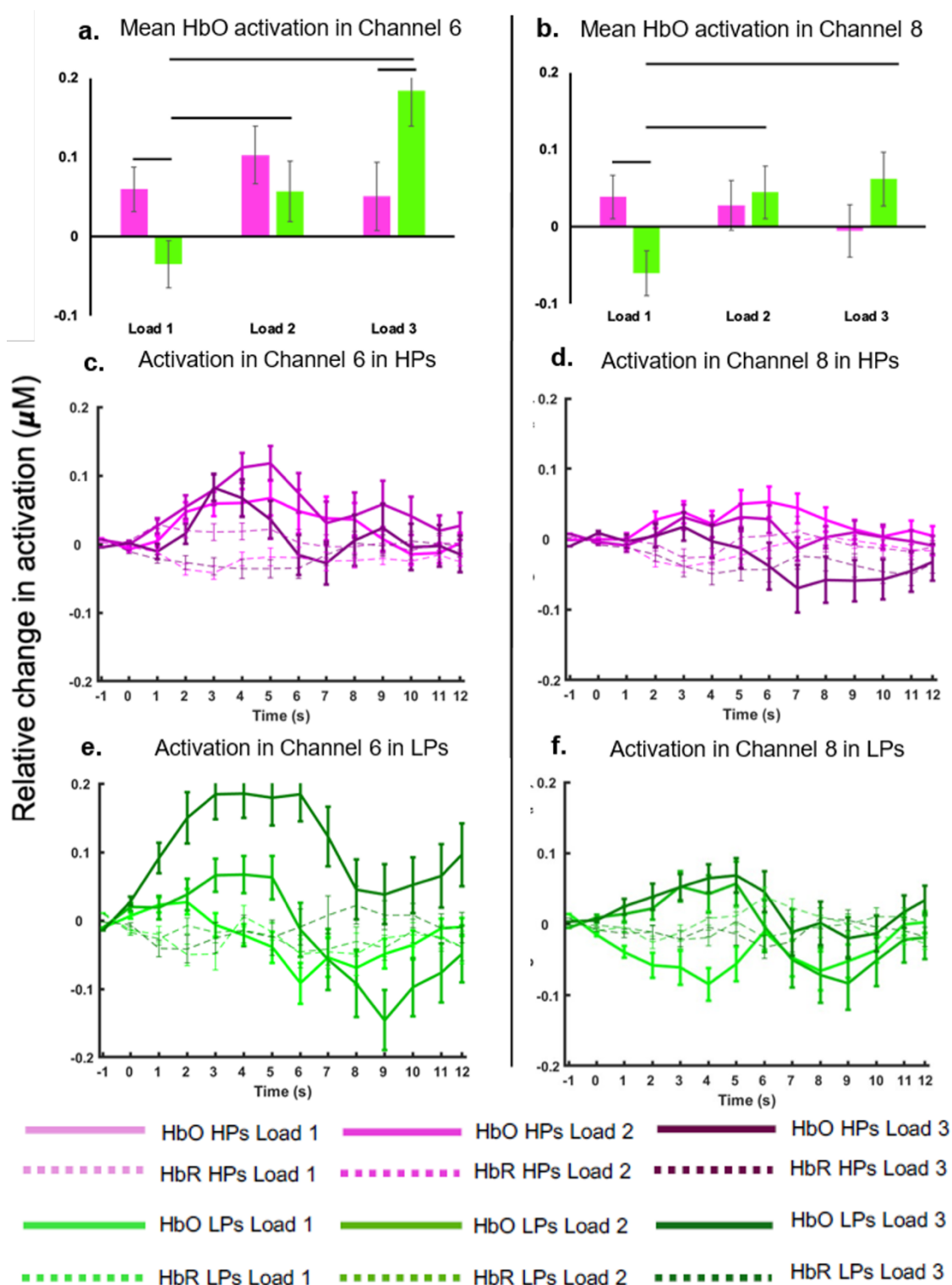
Figure 6. (a) and (b). Bar plots showing mean HbO activation for the time window between 3 s and 6 s for LPs (green) and HPs (magenta) in channel 6 and channel 8 (overlying the left frontal cortex) respectively. **(c) and (d)** Hemodynamic activation for HPs in channel 6 and channel 8 respectively. **(e) and (f)** Hemodynamic activation for LPs in channel 6 and channel 8 respectively. Error bars show 1 SE averaged over 1sec intervals. '-' indicates significance at $p<.05$.

a. Mean HbO activation in Channel 9

b. Mean HbO activation in Channel 11

c. Activation in Channel 9 in HPs

d. Activation in Channel 11 in HPs

e. Activation in Channel 9 in LPs

f. Activation in Channel 11 in LPs

Relative change in activation (μM)

Time (s)

HbO HPs Load 1   HbO HPs Load 2   HbO HPs Load 3
HbR HPs Load 1   HbR HPs Load 2   HbR HPs Load 3
HbO LPs Load 1   HbO LPs Load 2   HbO LPs Load 3
HbR LPs Load 1   HbR LPs Load 2   HbR LPs Load 3
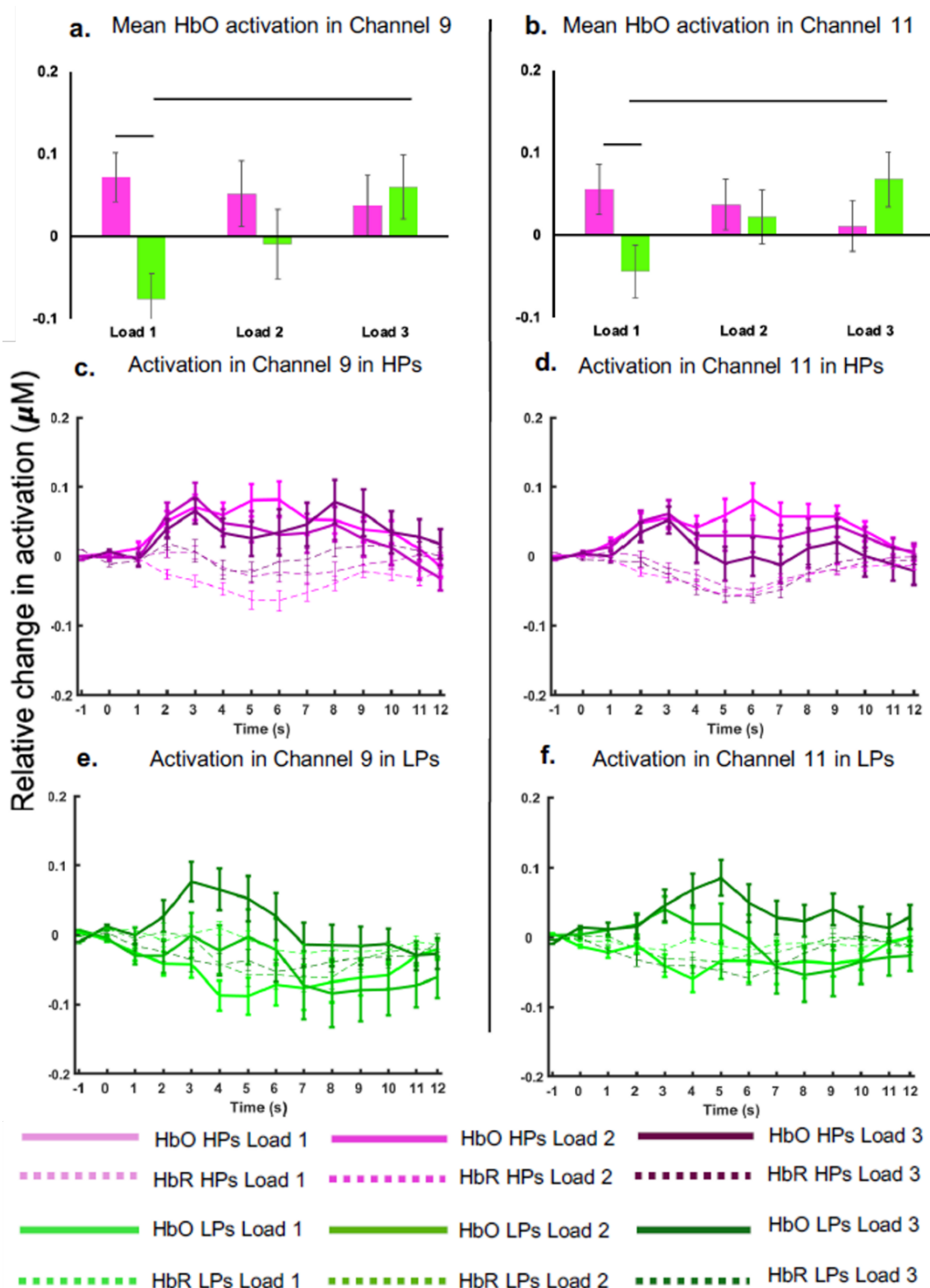
Figure 7. (a) and (b). Bar plots showing mean HbO activation for the time window between 3 s and 6 s for LPs (green) and HPs (magenta) in channel 9 and channel 11 (overlying the right parietal cortex) respectively. **(c) and (d)** Hemodynamic activation for HPs in channel 9 and channel 11 respectively. **(e) and (f)** Hemodynamic activation for LPs in channel 9 and channel 11 respectively. Error bars show 1 SE averaged over 1sec intervals. '-' indicates significance at $p < .05$.

a. Mean HbO activation in Channel 12

b. Mean HbO activation in Channel 14

c. Activation in Channel 12 in HPs

d. Activation in Channel 14 in HPs

e. Activation in Channel 12 in LPs

f. Activation in Channel 14 in LPs
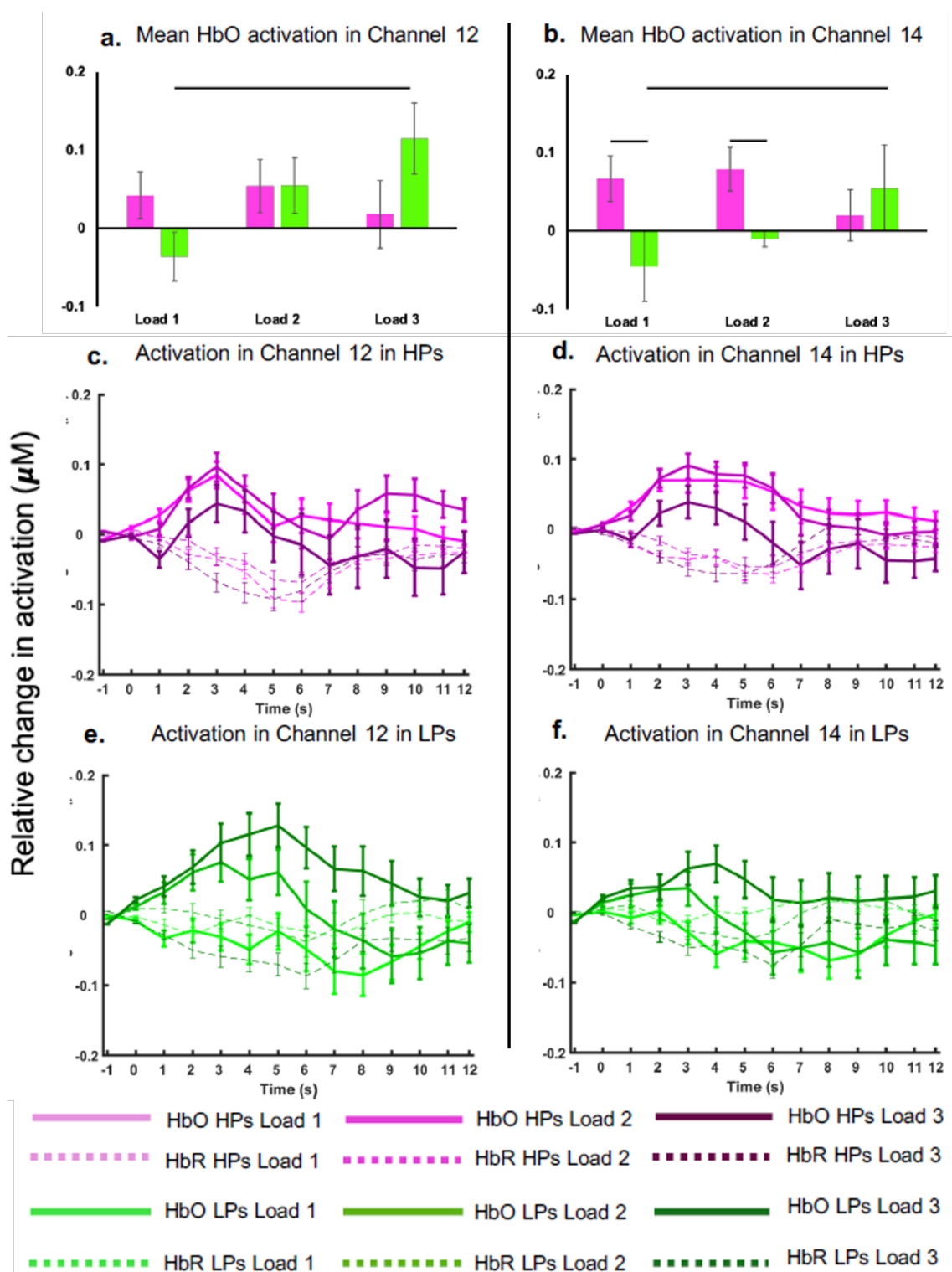
Figure 8. (a) and (b). Bar plots showing mean HbO activation for the time window between 3 s and 6 s for LPs (green) and HPs (magenta) in channel 12 and channel 14 (overlying the left parietal cortex) respectively. **(c) and (d)** Hemodynamic activation for HPs in channel 12 and channel 14 respectively. **(e) and (f)** Hemodynamic activation for LPs in channel 12 and channel 14 respectively. Error bars show 1 SE averaged over 1sec intervals. '-' indicates significance at $p<.05$.

2.4.3 Correlations between behavioural performance, brain activation, and parental questionnaires

We averaged activation across channels that showed a significant interaction between group, load and chromophore to create three brain clusters as they showed the same trend. The three brain clusters were left frontal cortex (averaging channel 6 and channel 8), right parietal cortex (averaging channel 9 and channel 11) and left parietal cortex (averaging channel 12 and channel 14). Next, we calculated the difference in activation between load 3 and load 1 in these brain areas (for each participant) as this key measure differentiated LPs from HPs. As expected, the difference in activation between loads in the three brain clusters was negatively correlated with maximum K suggesting that this association was still strong even when the variables were considered as continuous measures (see Appendix D, Figure D1). The difference in activation between loads in each of the three brain areas was correlated with data from the parental questionnaires. We pooled all 31 correlations and applied the Benjamini-Hochberg correction separately for each brain area (left frontal cortex, left parietal cortex, and right parietal cortex) with a false discovery rate of 0.1. Only those correlations that survived the Benjamini-Hochberg correction are reported. We found that the difference in activation between loads in the left parietal cortex was positively correlated with the life stress subscore from the Parenting Stress Index ($r = 0.293$, $p =.011$, see Figure 9). Life stress in this scale refers to any major life event that significantly increases life stress. We also found that the difference in activation between loads in the left parietal cortex was negatively associated with parental aspirations ($r = −0.323$, $p =$

0.006). Parental aspirations were the highest qualification parents hoped their children would achieve.
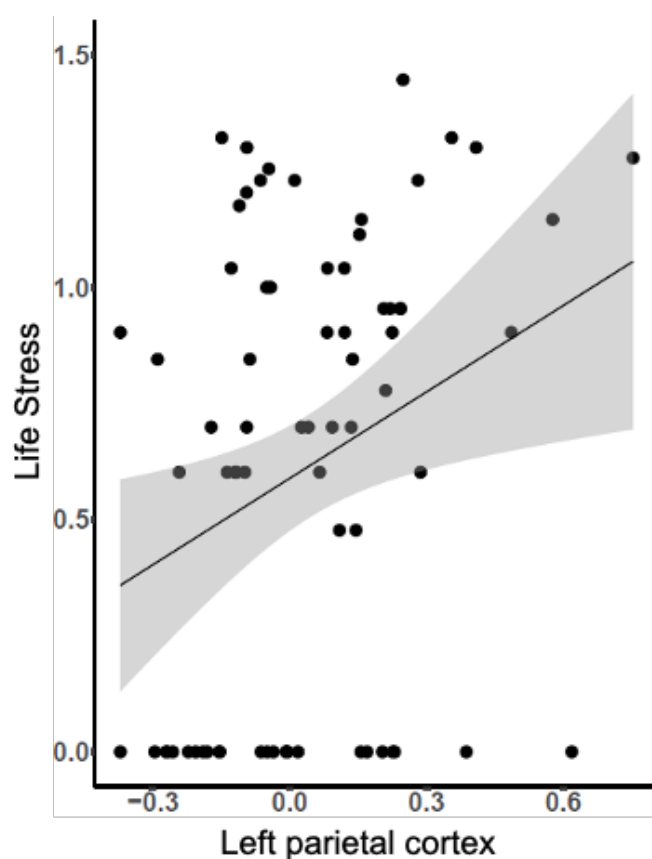
Figure 9. Plot showing a positive correlation between the difference in HbO activation in the left parietal cortex and the life stress subscore of the Parental Stress Index.

2.4.4 Mediation analyses

We conducted mediation analyses to further understand the association between behaviour, brain activation, and parental factors. Using mediation, we aimed to extend upon the two significant findings from the questionnaire correlation analyses and determine whether a trivariate relationship exists between behavioural performance, brain function and parental factors.

Concretely, we investigated if the difference in brain activation was a potential mediator between the distal predictor (parental factor) and the outcome measure (behavioural performance). According to Shrout and Bolger (2002), when a predictor is not experimental-based and distal in nature (e.g., home environment), an association between the predictor and the mediator is sufficient to warrant a test for mediation. Therefore, we focused on the significant bivariate relationships we identified from the correlation analyses described in the previous section: (1) the association between the life stress score and the difference in activation between loads in the left parietal cortex and (2) the association between parental aspirations and the difference in activation between loads in the left parietal cortex. For our analyses, we used the mediation function with bootstrapping in R. We found that the difference in activation between loads in the left parietal cortex partially mediated the relationship between life stress and maximum K (indirect path =-0.1429, p=.016). To determine if socioeconomic factors had an indirect effect on this association, we controlled for both parental education and income. This association remained significant even after accounting for parental education and income (p=.0014). Specifically, we found that higher life stress was related to a larger difference in activation between loads in the left parietal cortex, which in turn was related to lower maximum K. Next, we found that the difference in activation between loads in the same area partially mediated the relationship between parental aspirations and maximum K (indirect path =0.4643, p=.026). However, this mediation effect did not hold after controlling for parental education and income suggesting an influence of socioeconomic factors on the association between behavioural performance, brain activation and parental aspirations for their children.

2.5 Discussion

VWM is an essential cognitive system with a highly limited capacity that is reliably predictive of future academic achievements, making it important to understand the nature of individual differences in children (Bull et al., 2008; Swanson & Berninger, 1996). Critically, it is important to try to fullfil this objective in experimental designs without the effect of varying age within the cohort. In the

current study, we investigated how individual differences in VWM performance and brain function are linked to parental and home environment factors. We recorded behavioural and brain activation data from 4.5-year-old children with little variation in age as they completed a colour change-detection task in their homes. Our research also demonstrated the feasibility of collecting neural data on children in their homes. Home-based testing present with unique challenges that require experimenters to be creative while maintaining a standardized procedure. As examples, experimenters are required to manage space constraints while setting up equipment and to deal with distractions for themselves and the children being tested in a respectful manner in different households. Despite these difficulties, we attribute the low drop-rate to an efficient experimental design, extensive training in collecting behavioural and brain imaging data with children and the resourcefulness of the experimenters to maintain a good rapport with children and their parents to create a fun and engaging atmosphere where children did not feel they were being "tested".

In the current study, we observed load-dependent increases in accuracy and brain activation. In general, this finding is in agreement with previous VWM work in children and adults (Ambrose et al., 2016; Buss et al., 2014; Jha & McCarthy, 2000; Linden et al., 2003; Todd & Marois, 2004; Wijeakumar, Magnotta, et al., 2017). Our first critical question was to investigate whether differences in activation in the fronto-parietal network would underlie differences in behavioural performance. We found that LPs showed greater activation at load 3 than at load 1 in the left frontal, left parietal and right parietal cortices. By contrast, the HPs showed no modulation of activation between loads. HPs showed greater activation than LPs at load 1 across all three cortices and LPs showed greater activation than HPs at load 3 in the left frontal cortex. We posit that HPs were more 'prepared' through achieving a *heightened state of attention* eliciting greater activation at the lowest load (at the start of the experimental task) compared to the LPs. We further suggest that HPs were able to efficiently manage the more challenging demands of increasing VWM loads by utilizing similar levels of neural resources as they did not show any significant increases in activation. On the other hand, LPs showed increasing activation and poor

performance with increasing VWM load. We argue that LPs would have needed to *effortfully* attend to the demands of increasing VWM load by increasing activation and thus, recruited more neural resources. Critically, this increase in activation was not accompanied by an increase in performance in LPs, moving the interpretation away from a compensatory account of neurcognitive function often reported in older adults wherein greater neural resources are recruited to maintain the same performance as younger adults (Cabeza et al., 2018). In agreement with our finding, Honey and colleagues (2000) found that adults who performed poorly on a verbal WM task showed increased activation in the bilateral posterior parietal cortex. They surmised that this increase in parietal activation could be reflective of an increase in attentional demands and the use of visuospatial strategies. Along the same vein, Jaeggi et al. (2007) found that low-performing adults engaging in a challneging dual task displayed large load-dependent increases in activation when their capacity limitations were challenged. They reported that the increase in activation observed in low-performers was due to the additional recruitment of attentional and strategy-related resources. Further, they found that high-performers did not show an increase in activation with increasing task difficulty, which they suggested reflected more efficient processing. However, these findings are not in line with results from an adult study conducted by Nagel and colleagues (2009) who reported that young high-performing adults showed increasing activation with increasing load in a spatial WM task. In the current study, it is also possible that LPs were unable to suppress distraction or irrelevant information in the event of increasing task demands, thus increasing activation with a decline in performance. The inability to suppress distraction to irrelevant information and as a result, poorer VWM performance during a prefential looking task has been associated with greater activation in the frontal cortex in children in rural settings in India (Wijeakumar et al., 2019).

Our second critical question was to examine whether home environment and parental factors could shed light on the nature of individual differences in behaviour and associated brain activation. We found that the relationship between the frequency of stressful life events and poor behavioural performance

in the children in the VWM task was mediated by activation in the left parietal cortex. Higher life stress was measured as a greater number of stressful life events including but not limited to, divorce, change in job/school, death of a family member, and substance abuse. Further, this finding remained significant after we controlled for parent income and education, suggesting it is unrelated to socio-economic factors. Our finding is in line with an EEG study by Troller-Renfree and colleagues (2020) who found that infants of mothers who experienced higher chronic physiological stress showed altered brain activation patterns during the first year of life. They posit that maturational lags in development can persist into later life and have an effect on cognitive processing. Further, Hanson and colleagues (2012) assessed cumulative life stress in children and found a negative association with WM performance. It is also possible that stressful life events can signficantly affect the quantity and/or quality of time that parents spend with their children. Crnic and colleagues (2005) found that parent-reported life stress assesed over two years had a negative association with maternal parenting behaviour and the quality of parent-child interactions, which in turn contributed to poor behavioural functioning in children at age 5. Taken together, in the current study, we suggest that a greater number of stressful life events might cause instability in the child's life, resulting in changes to their cognitive processing. In a household with shifting/shifted stability, children might be constantly distracted and unable to consistently sustain attention and maintain information to efficiently accomplish goals or tasks. In addition, it is also possible that parents distracted by stressful life events might struggle to fulfil daily goals to manage care-taking and might transfer poor skills of goal maintenance and traits such as easy distractability to their children. It is important to acknowledge that such children who are negatively impacted by a stressful home environment might have yielded a more pronounced atypical brain-behaviour response since they were afterall subjected to home-based testing and assessments. We recommend that future studies should assess if brain-behaviour responses observed in such children during testing in their home environment can be similarly observed under controlled lab conditions.

In summary, our findings revealed that LP children showed a greater difference in activation between the low and high loads in a fronto-parietal VWM network. On the other hand, HP children did not show any modulation in activation with increasing VWM load. We also found that this difference in activation between loads in a left parietal cortex partially mediated the relationship between parent-reported life stress and VWM performance.

CHAPTER 3 DISENTANGLING AGE AND SCHOOLING EFFECTS ON VISUAL WORKING MEMORY DEVELOPMENT: AN fNIRS INVESTIGATION

3.1 Abstract

Formal schooling begins at an age where rapid developments in EF are already taking place. In order to be successful in school, children must exert control over their own behaviour, focus attention, and remember classroom rules and instructions. The objective of the current study was twofold: first to investigate whether the first year of formal schooling leads to improvements in EF, namely, VWM and its neural correlates, and second, to determine whether these improvements could predict academic success across time. Using a modified school cut-off design, behavioural data (measured with a colour change-detection task) and brain activation data (measured with fNIRS) were collected on two groups of children in their homes. Further, measures of academic success were also collected. At the first timepoint (T1), both groups of children were 4.5-years-old and in kindergarten ($Mage$ = 53.5 months, SD = 1.2). At the second timepoint (T2), one group (P1, N=39) had completed one year of schooling while the other group (KG, N=40) had remained in kindergarten. Results showed that across the year, P1 children made significantly greater improvements in VWM than KG children. Importantly, the two groups began the year with similar VWM, suggesting the difference between the two groups only emerged after exposure to formal schooling. Results also indicated that P1 children who began the year with better VWM gained more in vocabulary across the school year. Given that schooling is a learning context that places heavy demands on VWM in order to learn, children who began the year with better VWM made greater improvements in vocabulary across the school year. Taken together, these findings indicate exposure to formal schooling not only improves cognitive function but has important implications for subsequent academic success.

3.2 Introduction

The developmental time period between the ages of 4 and 7 is characterised by remarkable brain plasticity, sensitivity to environmental experiences and significant improvement across several neurocognitive domains (Fitzpatrick & Pagani, 2012). In many countries, this coincides with the start of formal schooling. In school, children are increasingly expected to exert greater control over their own behaviour, focus attention, and remember instructions – all of which fall under a cognitive process known as EF (Diamond, 2013). Solidifying our understanding of the relationships between neurocognitive functions, school experience, and academic success during this period is therefore critical to ensuring all children reach their full potential in education. The present study focuses on WM, a subcomponent of EF, and investigates how the first year of school impacts WM performance and its neural correlates and relates this to academic achievement.

Converging evidence has specifically linked WM to a variety of academic outcomes including numeracy and literacy (R. Bull & Scerif, 2001; Gathercole, Pickering, Knight, et al., 2004; Swanson & Beebe-Frankenberger, 2004). For instance, Fitzpatrick & Pagani (2012) found that early WM skills in toddlers were positively associated with later classroom engagement, number knowledge, and receptive vocabulary. Importantly, these associations remained significant after controlling for SES status and intellectual skills. Further, Bull et al. (2008) examined whether measures of WM in preschool children predicted later schooling achievement. Markedly, visual-spatial short-term memory span in pre-school was found to be a significant predictor of mathematic ability in first and third grade. Along a similar vein, Alloway and Alloway (2010) investigated the predictive power of WM and IQ in learning over a six year period and found that WM abilities at the start of formal education were a more powerful predictor of literacy and numeracy skills six years later than IQ. Critically, this study demonstrated WM is a cognitive skill dissociable from IQ with unique links to academic achievement. The authors concluded learning is an incremental process, and thus, the inability to retain information (resulting from poor WM) likely has negative ramifications for learning. Thus, it is evident that WM skills at

the start of formal schooling play an important role in determining subsequent school success. However, as neurocognitive development can be shaped by the environment that a child lives in (Noble et al., 2015), how might the schooling experience itself shape the development of WM? Roberts and colleagues (2015) sought to address this question by examining the extent to which chronological age and schooling duration were associated with verbal and visual-spatial WM in 6- to 7-year-old children. Assessments occurred over the year with schools quasi-randomly allocated to one of the four school terms. Raw scores were substantially higher in children who were assessed during term four, compared with children who were assessed during term one, even after adjusting for age and other potential confounders. The researchers concluded that the development of WM is strongly associated with time children have spent in the classroom, above and beyond their chronological age. Thus, exposure to a structured learning environment such as schooling may further bolster the developmental trajectory of WM (Brod et al., 2017; Zhang et al., 2019). For instance, children might rely on WM to follow directions, interact with peers, and keep track of routines (Diamond, 2013; Finch, 2019), all of which are important for school success (Burrage et al., 2008; Zhang et al., 2019). Although cross sectional research such as the study conducted by Roberts et al. (2015) provide some insight into the association between school experience and WM, longitudinal research allows for more direct causal relationships to be investigated.

An effective longitudinal method for exploring the impact of formal education on cognitive processes relies on the existence of specific cut-off dates imposed on school entrance. Cut-off designs provide a naturalistic way to measure the impact of schooling by comparing two groups of children that are similar in age but, due to fixed entry dates, are enroled into different school years. Several studies have employed the cut-off design and found a positive effect of schooling on numeracy (Bisanz et al., 1995; Christian et al., 2000) and literacy skills (Frederick J. Morrison et al., 1995; Varnhagen et al., 1994). However, only one cut-off study has focused specifically on how attending formal schooling may shape WM skills. Burrage et al. (2008) administered tasks

assessing response inhibition and WM in a sample of American children and found children who attended school had better WM at the end of the year than children who stayed in kindergarten. However, these findings should be interpreted with caution as the schoolers also outperformed the kindergartners at the start of the year, and this was not controlled for in their analyses. Specifically, the analysis did not compare the mean *change* within each group, and thus is it unclear whether the growth shown by the schoolers was greater than the growth shown by the kindergartners. If the schooling environment did in fact increase WM skills, children who went to school should have shown greater change across the year than the kindergartners. The authors also suggested the baseline difference may have been due to a combination of prior experiences and/or home practices in the group that attended school. However, this interpretation implies that parents of soon-to-be schoolers increase reading or numeracy exercises, which hinges on the assumption that reading or maths causally affects WM. Previous longitudinal research conducted by Gathercole et al. (1992) casts doubt on such an interpretation. Specifically, these researchers examined the relationship between WM and vocabulary in 4- to-8- year-old children and found that WM abilities at 4-years-old were significantly associated with vocabulary at age 5-years-old. In contrast, vocabulary at 4- years-old was only weakly linked to WM processing at 5-years-old, suggesting that there might only exist a unidirectional association between WM processing and vocabulary.

The current study attempts to reconcile previous methodological and interpretational issues and fill the knowledge gap surrounding the relationship between WM, formal schooling, and academic success. First, children were assessed during the summer before school began, to ensure a suitable baseline measure was included. Second, vocabulary and numeracy assessments were included which served as measures of academic achievement. Additional school achievement packs assessing phonetic awareness and mathematical ability were also included as outcome measures to determine how much the P1 children learned across the school year. Lastly, both behavioural and fNIRS data were collected on children while they

completed a VWM task in their homes. The fNIRS system was selected for this investigation due to its practicality, portability and efficacy in measuring the neural processes underlying VWM in young children (Buss et al., 2014, 2018; Tsujimoto et al., 2004).

By combining brain and behavioural measures, the current study aims to determine whether there are neurocognitive benefits associated with entering formal schooling. Brod and colleagues (2017) assessed behavioural performance and brain function underlying IC in two groups of 5-and 6-year-old children; one group completed one full year of schooling while the other group stayed in kindergarten. A larger increase in activation in the right superior PPC, an area associated with sustained attention, was found for children who attended school. The authors proposed that schooling places increased demands on sustained attention, resulting in greater activation in the PPC. Although this study did not include a WM task, it might implicate the involvement of WM processing for a few reasons. First, the association between attention and WM plays a role in models of WM processing, with both attentional control and attentional focus being important components (Unsworth & Spillers, 2010). Specifically, attentional control helps to actively maintain relevant information and not succumb to distraction (Engle & Kane, 2003; Kane et al., 2012). Second, tasks assessing both sustained attention and WM processing are associated with parietal activation (Berryhill, 2012; Corbetta & Shulman, 2002; Curtis, 2006; Malhotra et al., 2009; Öztekin et al., 2009). Third, meta-analyses employing activation likelihood estimation have shown that there is spatial overlap between regions of interest in the parietal cortex activated in studies investigating WM and IC (Niendam et al., 2012). Lastly, a dynamic field computational model initially developed to understand VWM processing in children, younger adults, and older adults was capable of capturing behavioural performance and changes in brain activation in an IC task (Wijeakumar et al., 2017). This finding is in line with the argument that inhibition is a property of spatially distributed functional networks that support general WM processes (Erika-Florence et al., 2014).

To isolate the unique contributions of schooling on VWM processing and academic achievement, structural equation modelling (SEM), a powerful tool used to represent, estimate, and test relationships between variables (Rigdon, 1998) was employed in the current study. Specifically, SEM is used to understand the patterns of variance and covariance between variables and explain as much of this variance as possible (Kline, 2001). It is a flexible method that places few constraints on the types of relationships that can be investigated. Unlike other traditional statistical methods which specify a default model, SEM requires the researcher to formally specify a model, which is then compared to the observed data (Suhr, 2006). The degree to which the model can reproduce the overserved data is taken as evidence for or against the model (Kievit et al., 2018). Further, this framework allows directional and nondirectional relationships among measured data (represented by observed variables), and theoretical constructs (represented by latent variables) to be investigated (MacCallum & Austin, 2000). Several different types of models exist within the SEM framework. The current study employed a specific subtype of longitudinal SEM called latent change score (LCS) models (Kievit et al., 2018; McArdle & Hamagami, 2004) which have been used to test a wide range of developmental hypotheses. This type of model was selected as it requires at least two timepoints, can model the change in a single domain and can model the change in two domains, known as cross-domain coupling.

The current study employed a modified cut-off design to investigate whether the first year of formal schooling results in an improvement in VWM performance and underlying changes in brain activation and determine whether this is associated with an improvement in academic achievement. In Scotland, the starting school year cohort consists of children born between the beginning of March in one year (starting at around 5.5 years) and the end of February the following year (starting at around 4.5 years). However, the parents of children born in January and February can choose to defer their child's entry and these requests are automatically approved. Consequently, two groups of children were tested across two years; one group enroled into school as soon as they became eligible and completed Primary 1 (P1) between the two measurement

occasions. The other group did not enrol into school and remained in kindergarten (KG). At timepoint 1 (T1), both groups of children were in kindergarten and at timepoint 2 (T2), P1 children had finished one year of schooling and KG children had completed another year in kindergarten. Based on previous findings that have consistently reported age-related improvements in VWM (Buss et al., 2014; Pailian et al., 2016; Simmering, 2012), literacy (Biemiller & Slonim, 2001; Rowe et al., 2012), and numeracy (Aubrey & Godfrey, 2003; Aunio & Niemivirta, 2010), it is predicted that across the year, both P1 children and KG children will improve in all tasks. Several schooling-related hypotheses were also tested. Based on reports by Roberts and colleagues (2015) that suggests school duration is positively associated with verbal and visuo-spatial WM skills, it is hypothesized that P1 children will show greater improvements in VWM performance and academic achievements than KG children. Further, based on work by Alloway and Alloway (2010) that found WM abilities at the start of formal education were predictive of literacy and numeracy skills six years later, it is hypothesized that VWM performance would predict academic achievements in P1 children. Lastly, in line with findings in Chapter 2 that found poorer VWM performance was related to a greater modulation of activation in cortical areas of the fronto-parietal network, it is expected that KG children (showing poorer VWM performance) will show more dramatic modulation of activation in the frontal and parietal regions.

3.3 Methods

3.3.1 Participants

Please refer to Chapter 2 (section 2.3.1) for detailed recruitment information and criteria for inclusion. All children included in the study were born in January or February 2014. The research was approved by the General University Ethics Panel (GUEP 375A – see Appendix E) at the University of Stirling.

Children were tested on two separate occasions, across two consecutive years. At T1, 95 4.5-year-olds (45 females, *M*age = 53.5 months, *SD* = 1.2) were recruited for the study. Sixteen children were excluded from all analyses;

13 (6 P1, 7 KG) children interfered with the neuroimaging set-up (pulled the cap off) before the completion of the task, 3 provided unusable fNIRS data (two KG children had thick hair that prevented contact between the optodes and the scalp and caused poor signal quality, and data from one P1 child was lost due to experimenter error). Hence, a total of 79 children (39 females, Mage at T1 = 53.5 months, SD = 1.3, range = 5 months) provided potentially usable fNIRS data at T1 (see further analysis-specific criteria below). All 79 children agreed to take part at T2 (39 females, Mage = 65.5 months, SD = 1.1, range = 5 months). Of these children, 39 (24 females, Mage at T1 = 65.7 months, SD = 1.1, $range$ = 5 months) attended P1 in between the two timepoints, and 40 (14 females, Mage at T1 = 65.4 months, SD = 1, $range$ = 5 months) remained in KG. The age of the two groups at test did not differ significantly, $t(78)$= 1.142, p =.257.

Parental educational attainment was high for both the P1 and KG groups. Specifically, 95% of P1 children and 95% of KG children had at least one parent who attained a BSc degree or higher. In 2019, the average household disposable income in the UK was £35,900 (Office for National Statistics, 2020). The net annual household income was higher than the national average for both the P1 group (M = 7 (category £60,000 – 70,000), SD = 2) and the KG group (M = 7 (category £60,000 – 70,000), SD = 3), and the groups did not differ significantly $t(75)$= .201, p =.841.

fNIRS exclusion (see Figure 10):

VWM. For the VWM analyses, five children (two P1, three KG) were excluded for refusing to complete the task at T1, and data from one KG child was lost due to experimenter error at T2. Thus, 73 children (36 females, Mage at T1 = 53.5 months, SD = 1.3) contributed longitudinal data for the VWM fNIRS analyses. Of these children, 37 (23 females, Mage at T1 = 53.7 months, SD = 1.4, $range$ = 5 months) attended P1 in between the two timepoints, and 36 (13 females, Mage at T1 = 53.3 months, SD = 1.2, $range$ = 5 months) remained in KG.

Behavioural exclusion (see Figure 10):

Vocabulary. For the vocabulary analyses, one KG child was excluded for refusing to complete the task at T1, and data from one KG child was lost due to experimenter error at T2. 77 children (38 females, *M*age at T1 = 53.5 months, *SD* = 1.3, range = 5 months) contributed longitudinal data for the vocabulary analyses. Of these children, 39 (24 females, *M*age at T1 = 53.6 months, *SD* = 1.3, *range* = 5 months) attended P1 in between the two timepoints, and 38 (14 females, *M*age at T1 = 53.3 months, *SD* = 1.2, *range* = 5 months) remained in KG.

      Numeracy. For the numeracy analyses, four children (one P1, three KG) were excluded for refusing to complete the task at T1, and data from one KG child was lost due to experimenter error at T2. 74 children (35 females, *M*age at T1 = 53.5 months, *SD* = 1.2, range = 5 months) contributed longitudinal data for the numeracy analyses. Of these children, 38 (23 females, *M*age at T1 = 53.7 months, *SD* = 1.3, *range* = 5 months) attended P1 in between the two timepoints, and 36 (12 females, *M*age at T1 = 53.2 months, *SD* = 1.1, *range* = 5 months) remained in KG.

      School achievement packs (T2 only). No children were excluded.
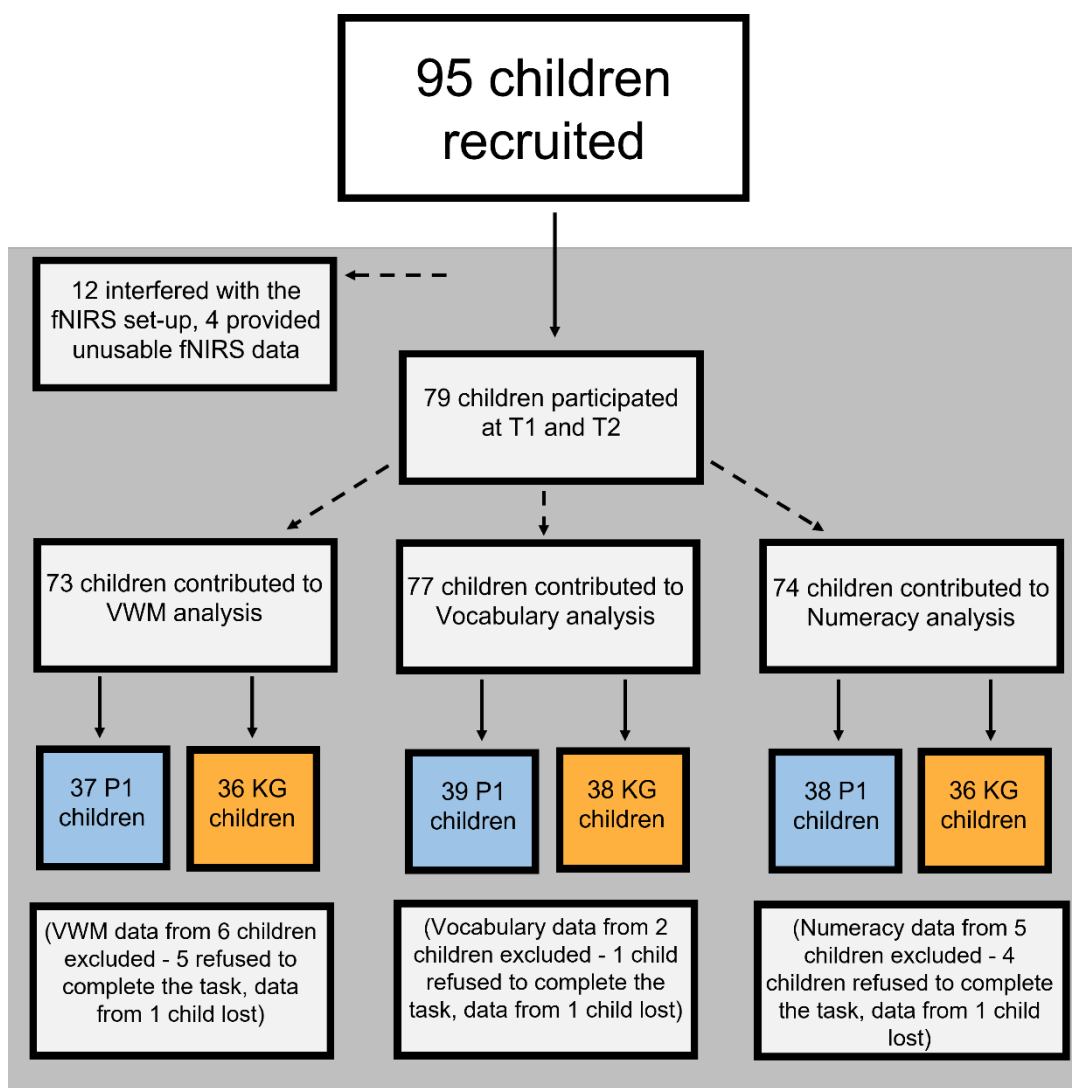
Figure 10. Schematic of participant recruitment and engagement across the two timepoints.

3.3.2 Experimental task

Visual working memory task

VWM was assessed using the colour change-detection task by Simmering (2012). Specific task details can be found in Chapter 2 (section 2.3.2). Loads were classified into low, medium and high at each of time timepoints (at T1: low = 1 item, medium = 2 items and high = 3 items and at T2: low = 2 items, medium = 3 items and high = 4 items). VWM load was different between both timepoints to avoid ceiling effects and maintain challenging conditions as the

children became older. Each load featured randomised presentations of 8 same and 8 different trials.

3.3.3 Academic performance measures

Vocabulary task

The vocabulary subset of the Wechsler Preschool and Primary Scale of Intelligence (Warschausky & Raiford, 2018) was used to assess word knowledge. The task included 3 picture items and 20 verbal items. During the picture items, children were presented with 3 consecutive pictures of objects (car, scissors, banana) and asked to name each object. If a child incorrectly named the first object (car), they were corrected. Feedback was not provided for the other two picture items. For the verbal items, children were required to provide verbal definitions of words. Corrective feedback was given for the first two verbal items if a child did not receive a perfect score. No feedback was provided for the remaining verbal items. In accordance with the manual, if a child's response was unclear or too vague, the experimenter prompted the child by asking, "What do you mean", or "Tell me more about it", or some other neutral query. The test was discontinued if a child gave three consecutive incorrect responses. The task was repeated at T2. Correct responses were summed to provide a total vocabulary score out of 43 possible points. Scores were calculated separately at T1 and T2.

Numeracy task

The numeracy screener described by Nosworthy and colleagues (2013) was used to assess basic numeracy skills. Children were instructed to compare pairs of magnitudes ranging from one to nine and judge which was larger. Magnitudes were represented symbolically (56 digit pairs) and non-symbolically (56 pairs of dot arrays). In both the symbolic and non-symbolic conditions, numerical magnitude was counterbalanced for the side of presentation. Dot stimuli were also controlled for area and density. Easier items were presented

first, followed by more difficult items. Children were given one minute to complete the symbolic condition, and one minute to complete the non-symbolic condition. The symbolic and non-symbolic conditions were counterbalanced across individuals. The task was repeated at T2. Children received one point for each correct answer. A final score was calculated at each timepoint by subtracting incorrect responses from correct responses.

School achievement packs (T2 only)

Two measures of achievement were included to assess how much P1 children learned over the course of the year in terms of school content. The math pack contained 25 math questions, adapted from the Scottish Curriculum For Excellence teaching resources (*twinkl*, n.d.). The test was discontinued after 3 incorrect responses. The phonemes pack contained 20 questions assessing phonetic awareness, adapted from the Heggerty Phonemic Awareness Program (Heggerty, 2019). The pack included 10 items requiring the addition of a phoneme, and 10 items requiring the substitution of a phoneme. A final score for each pack was calculated by summing the correct responses.

3.3.4 fNIRS data acquisition and pre-processing

The method for acquiring fNIRS data and processing the signals remained the same for T1 and T2. Details can be found in Chapter 2 (section 2.3.3 and section 2.3.7, respectively).

3.3.5 Procedure

For the VWM task, the procedure remained the same between the timepoints. For more details on the full procedure, refer to Chapter 2 (section 2.3.4). Once children completed the VWM task, they were given the I-pad© to watch cartoons while the researchers removed the cap. After a short break, children were told they would be playing a word game (vocabulary task). The researchers began the task by presenting the picture items, followed by the

verbal items. Next, children were told they would be playing a numbers game (numeracy task). The task began with the symbolic practice items where children were instructed to cross out the bigger of two numbers. After the experimenter reviewed the practice items and corrected any mistakes, children were given one minute to complete the symbolic test items. Children were then instructed to complete the non-symbolic practice items, by crossing out the square that contained the most dots. After the experimenter reviewed the practice items and corrected any mistakes, children were given one minute to complete the non-symbolic test items. Next, children were told they would be listening to some word sounds (phonemes pack – only administered at T2) followed by some math questions (math pack – only administered at T2). The VWM task was always administered first, but the order in which the vocabulary and numeracy tasks were presented was counterbalanced. Children were rewarded with stickers after completing each task, regardless of their performance. All children were remunerated with £10 and a toy upon completion of each time point measurement.

3.3.6 Behavioural analyses

Visual working memory

Accuracy (A') and capacity (K) were calculated from the hits (H) and false alarms (FA) based on the behavioural responses. A' was calculated for each load using Grier's (1971) formula, updated by Aaronson and Watts (1987), where A' = 1 indicates perfect performances, and A' = 0.5 indicates chance performance.

K was calculated for each load using Pashler's (1988) formula. K represents the number of items that are successfully stored in WM. Maximum K was estimated as the highest K value across all loads.

More detailed information regarding the specific formulas can be found in Chapter 2 (section 2.3.6).

3.3.7 Outlier correction

All behavioural data were screened for outliers. To correct for longitudinal outliers, we used the Mahalanobis distance method at a threshold of $p<.001$. Further, we identified outliers that were + or – 3 SDs from the mean at each timepoint. Subjects that were identified as outliers across both methods were removed before LCS modelling. Six outliers were identified: three in the VWM task (two P1, one KG), two in the phonemes pack (two P1) and one in the math pack (one KG).

3.3.8 fNIRS group analyses

Only correct trials were included in the fNIRS group analyses. The hemodynamic response was classified into an early phase window, ranging from the 3rd to 6th second. This time window was selected based on findings from Buss and colleagues (2014) and on observations of the peak of the hemodynamic response of the task. More details can be found in Chapter 2 (section 2.3.8).

The mean haemodynamic activation for each load (T1: loads 1, 2, 3; T2: loads 2,3,4), trial type (same, different), chromophore (HbO, HbR), and channel (1 to 14) within each participant (T1: N=74, T2: N=79) was calculated. At T1, the mean number of correct trials included per participant was 15 ± 0.14 trials for load 1, 13 ± 0.29 trials for load 2 and 11 ± 0.23 trials for load 3. At T2, the mean number of trials included per participant was 15 ± 0.15 trials for load 2, 13 ± 0.26 trials for load 3 and 11 ± 0.25 trials for load 4.

3.3.9 Modelling framework

A series of univariate LCS models were fitted to each of the tasks to investigate the degree of change within each domain. This is the simplest type of LCS model, as it uses a single variable measured on two occasions. Importantly, the model was set up as a multi-group model, meaning the same model is fitted to

the two groups separately, allowing the key parameters to be estimated independently. The basic equation of the model is as follows:

$$X_{i,t2} = X_{i,t1} + \Delta X_{i,1}$$

where an individual's score *(i)* on a domain *(X)* at timepoint 2 *(t2)* is equal to the sum of the individual's score at timepoint 1 *(t1)* and the change, or difference score (ΔX_i). By fixing the autoregressive parameter between T1 and T2 to 1, we assume that intervals are equidistant across individuals (Kievit et al., 2018). The change score equation can be simplified to:

$$\Delta X_{i,1} = X_{i,t2} - X_{i,t1}$$

A critical requirement for model specification is to establish a scale for each latent factor. This can be done by fixing the value of a parameter associated with the latent variable to 1. Thus, the LCS factor (ΔX_i) is measured by timepoint 2, with a factor loading fixed to 1. The change between T1 and T2 is captured by the mean of the LCS factor, while the extent to which individuals differ in the amount of change they manifest is captured by the variance. Lastly, a covariance or regression parameter is added to the change score, to determine whether the amount of change depends on scores at timepoint 1:

$$\Delta X_{i,1} = \beta * X_{i,t1}$$

Thus, this model provides three key pieces of information (see Figure 11): (1) whether there is significant average change across the timepoints, as determined by the mean of the LCS factor ($\mu_{\Delta X}$), (2) whether individuals differ in how much they change, as determined by the variance ($\sigma^2_{\Delta X}$), and (3) whether the change is dependent on scores at T1, as determined by the covariance / regression parameter ($\beta_{XT1\Delta X}$). Importantly, this kind of model is just-identified, meaning as many unique pieces of information are entering the model as parameters to be estimated (Kievit et al., 2018). Thus, model fit cannot be assessed unless additional pieces of information are included, such as an extra timepoint. Nevertheless, important questions can be investigated by employing parameter constraints. Here, the key question is to determine whether the two groups (P1 and KG) differ in the amount of change they exhibit in a specific

domain (i.e. VWM) across timepoints. Thus, one model allows the change in both groups to differ (just-identified model), and a second model constrains the change to unity (constrained model). If constraining the change to unity leads to a significant drop in model fit (as indexed by the chi-square value), it would indicate that the two groups differ in how much they change.

Next, by adding an extra domain, the univariate LCS model becomes a bivariate LCS model (see Figure 11). The equation becomes:

$$\Delta X1_{i,1} = \beta1 * X1_{i,t1} + c * X2_{i,t1}$$

where the change scores of two domains (*X1* and *X2*) are a function of two processes: the self-feedback parameter *(β)* within each domain, and a coupling effect *(y)* between the two domains. This bivariate model provides the same three key pieces of information outlined above, but for two different domains. Further, it provides an additional four pieces of information, (1) whether the scores in *X1* are associated with the scores in *X2* at T1, as determined by the intercept covariance (ρ_{X1X2}) (2) whether the change in X1 is associated with the change in *X2*, as determined by the change covariance $(\rho_{\Delta X1 \Delta X2})$ (3) whether the change in *X1* is a function of the starting point of *X2,* as determined by the coupling effect $(y1_{X2\Delta X1})$, and (4) whether the change in *X2* is a function of the starting point of *X1*, also determined by the coupling effect $(y2_{X1\Delta X2})$. Thus, this bivariate extension allows an investigation into the degree to which change in one domain (i.e. vocabulary) is a function of the starting point in another domain (i.e. VWM), or vice versa, or both.
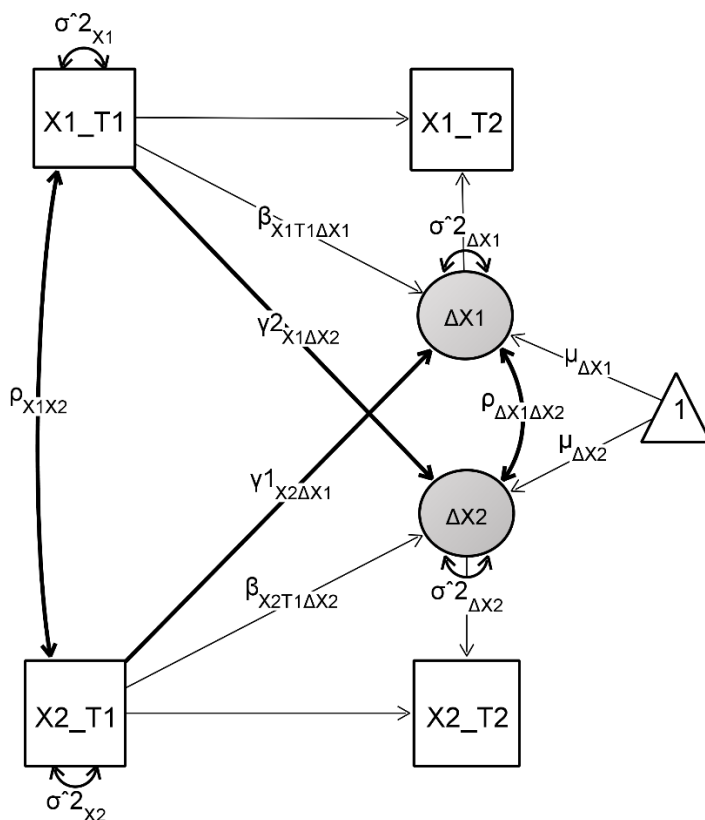
Figure 11. Graphical illustration of a bivariate LCS model. Observed variables are depicted as squares and latent variables as circles. Variances are shown by two-headed arrows and regressions are shown by one-headed arrows. Unmarked paths are fixed to 1. Figure created in Onyx (http://onyx.brandmaier.de).

3.3.10 Model fit indices

Models were estimated in the lavaan software package in R (version 3.6.2, 2019; Rosseel, 2012). Full information maximum likelihood was used for model estimation and to handle missing data. To test for the significance of parameters of interest, an equality constraint was made on the parameter and the change in model fit was assessed using the chi-square difference test. To account for age and gender effects, these variables were added as covariates of interest into all models.

3.4 Results

3.4.1 Behavioural results – Univariate LCS modelling

Five separate univariate models were fitted to each group (P1 and KG) with (1) maximum K estimates (2) average A' (3) vocabulary scores (4) symbolic numeracy scores (5) non-symbolic numeracy scores. Parameter estimates are shown in Table 2 and Table 3, and mean estimates are illustrated in Figure 12.

Maximum K. Both P1 children and KG children showed a significant increase in maximum K between T1 and T2. There was no significant change in model fit when the change in maximum K was constrained to be equal across groups. Additionally, there was no significant change in model fit when the baseline scores at T1 were constrained to be equal across groups. This suggests that P1 children and KG children began the year with similar maximum K estimates, and they changed equally between the two timepoints.

A'. Unlike with maximum K, A' estimates were available for each load. To make an informed decision about whether A' at specific load(s) needed to be moved into univariate modelling, a repeated measures ANOVA with within-subject factors of load (low, medium and high) and timepoint (T1 and T2) and a between-subjects factor of schooling group (P1 and KG) was run. A main effect of load, $F (1,138) = 76.6$, $p = .000$, $\eta p^2 = 0.526$, was observed. Further, there was a significant interaction between timepoint and schooling group (F $(1,69) = 6.35$, $p = .014$, $\eta p^2 = 0.084$) but no interaction between timepoint, schooling group and load. Thus, A' estimates across low, medium and high loads were averaged to create an overall mean A' estimate for each participant and timepoint. These average A' estimates were used in univariate modelling. Note that, average A' represented how well a child did on the VWM task as a whole.

Average A'. P1 children showed a significant increase between T1 and T2, while KG children did not change significantly. Constraining the change to be equal across groups led to a significant drop in model fit, as indexed by the chi-square value $\Delta x^2 = 9.660$, $\Delta df = 1$, $p = .002$, suggesting the two groups differed in how much they changed from T1 to T2. To follow up on this group

difference, the change in P1 children was constrained to zero which led to significantly worse model fit Δx^2 = 6.249, Δdf = 1, p = .012, confirming P1 children improved between the timepoints. Further, constraining the change in KG children to zero lead to a trend drop in model fit for KG children Δx^2 = 3.784, Δdf = 1, p = .052. Constraining T1 scores to be equal across groups did not lead to a significant drop in model fit, confirming P1 children and KG children began the year with similar average A'.

Vocabulary. Both P1 children and KG children showed a significant increase in scores between the two timepoints. Constraining the change in both groups to be equal led to a significant drop in model fit Δx^2 = 4.476, Δdf = 1, p = .034, suggesting P1 children increased significantly more than KG children. To follow up on this group difference, the change in each group was constrained to zero. This led to significantly worse fit for both P1 children Δx^2 = 27.420, Δdf = 1, p < .001, and KG children Δx^2 = 9.331, Δdf = 1, p = .002, suggesting that both groups improved over time. Importantly, the improvement in P1 children was greater than the improvement in KG children. No significant baseline differences were found.

Numeracy. Separate univariate models were fitted for symbolic and non-symbolic numeracy conditions using children's respective scores. For the symbolic condition, both P1 children and KG children showed a significant increase in scores between T1 and T2. No significant changes in model fit were found when the change was constrained to be equal across groups. Further, no significant baseline effects were found when the scores at T1 were constrained to be equal across groups. For the non-symbolic condition, P1 children significantly improved between the two timepoints while KG children did not. No significant drop in model fit was observed when the change was constrained to be equal across groups. Further, no significant changes in model fit were found after constraining T1 estimates to be equal across groups. Thus, for both conditions of the task, P1 children and KG children started out with similar scores and they changed comparably between the two timepoints.

School achievement packs. Univariate models could not be fitted to the school achievement packs as they were only administered at T2, after P1 children had completed 1 year of schooling. Thus, simple t-tests were conducted to compare performance between P1 and KG children on these measures. As expected, P1 children (*M* = 30.1, *SD* = 6.6; *M* = 6.4, *SD* = 4) performed significantly better than KG children (*M* = 23.9, *SD* = 6.5; *M* = 2.5, *SD* = 2.7) on both the math and phonemes packs, respectively (t[77] = 4.233, *p* <.001; t[76] = 5.067, *p* <.001).

Table 2. Parameter estimates for P1 children and KG children from two separate univariate models on the colour change-detection task. Standard errors are in parentheses. [*]Asterisks denote significance at *p* <.05 level. [a] Age = age in days. [b] Gender coded as 1 = girls , -1 = boys.

	Maximum K		Average A'	
	P1	KG	P1	KG
Mean change $\mu_{\Delta X}$	.72* (.12)	.66* (.12)	.02* (.01)	-.02 (.01)
Change variance $\sigma^2_{\Delta X}$	.57* (.11)	.57* (.15)	.0* (.0)	.01* (.0)
Intercept X_T1	6.16 (3.35)	-1.32 (4.02)	.92* (.45)	-.13 (.54)
Intercept variance σ^2_X	.42* (.09)	.24* (.06)	.0* (.0)	.0* (.0)
Intercept-change covariance $\beta_{XT1\Delta X}$	-.26* (.08)	-.12* (.06)	-.0* (.0)	-.0* (.0)
Age[a] onto intercept	-.25 (.2)	.2 (.25)	-.0 (.03)	.06 (.03)
Age-change covariance	-.03 (.04)	-.0 (.05)	-.0 (.0)	-.0 (.0)
Gender[b] onto intercept	.06 (.11)	.08 (.09)	.01 (.01)	-.0 (.01)
Gender-change covariance	.01 (.13)	-.02 (.12)	-.01 (.01)	-.06 (.05)

Table 3. Parameter estimates for P1 children and KG children from three separate univariate models on the academic achievement tasks. [*] Asterisks denote significance at p <.05 level. [a] Age = age in days. [b] Gender coded as 1 = girls , -1 = boys.

	Vocabulary		Numeracy (Symbolic)		Numeracy (Non-Symbolic)	
	P1	KG	P1	KG	P1	KG
Mean change $\mu_{\Delta X}$	9.62* (1.18)	5.63* (1.38)	9.13* (1.54)	6.84* (1.74)	6.2* (1.48)	2.04 (1.63)
Change variance $\sigma^2_{\Delta X}$	53.99* (13.63)	67.97* (21.52)	89.24* (20.83)	108.9* (28.14)	80.63* (19.47)	96.45* (20.98)
Intercept X_T1	-100.24* (31.68)	-94.12* (44.02)	69.21 (47.6)	-80.78 (66.42)	-11.43 (51.06)	-43.1 (71.9)
Intercept variance σ^2_X	31.34* (6.69)	47.55* (7.59)	78.23* (24.71)	58.85* (13.52)	66.43* (14.3)	64.1* (14.59)
Intercept-change covariance $\beta_{XT1\Delta X}$	-27.34* (8.52)	-35.71* (10.88)	-58.62* (21.04)	-56.12* (14.57)	-51.7* (13.11)	-58.53* (16.9)
Age[a] onto intercept	7.15* (1.93)	6.95* (2.68)	-4 (2.9)	5.71 (4.08)	1.83 (3.11)	3.74 (4.41)
Age-change covariance	-1.01* (.45)	.08 (.36)	.43 (.55)	-.67 (.45)	-.48 (.56)	-.12 (.47)
Gender[b] onto intercept	.64 (.92)	.4 (1.17)	.71 (1.54)	-.54 (1.51)	.6 (1.47)	.3 (1.77)
Gender-change covariance	-.73 (1.12)	-.95 (1.39)	-1.64 (1.48)	1.54 (1.91)	-1.54 (1.53)	.36 (1.75)
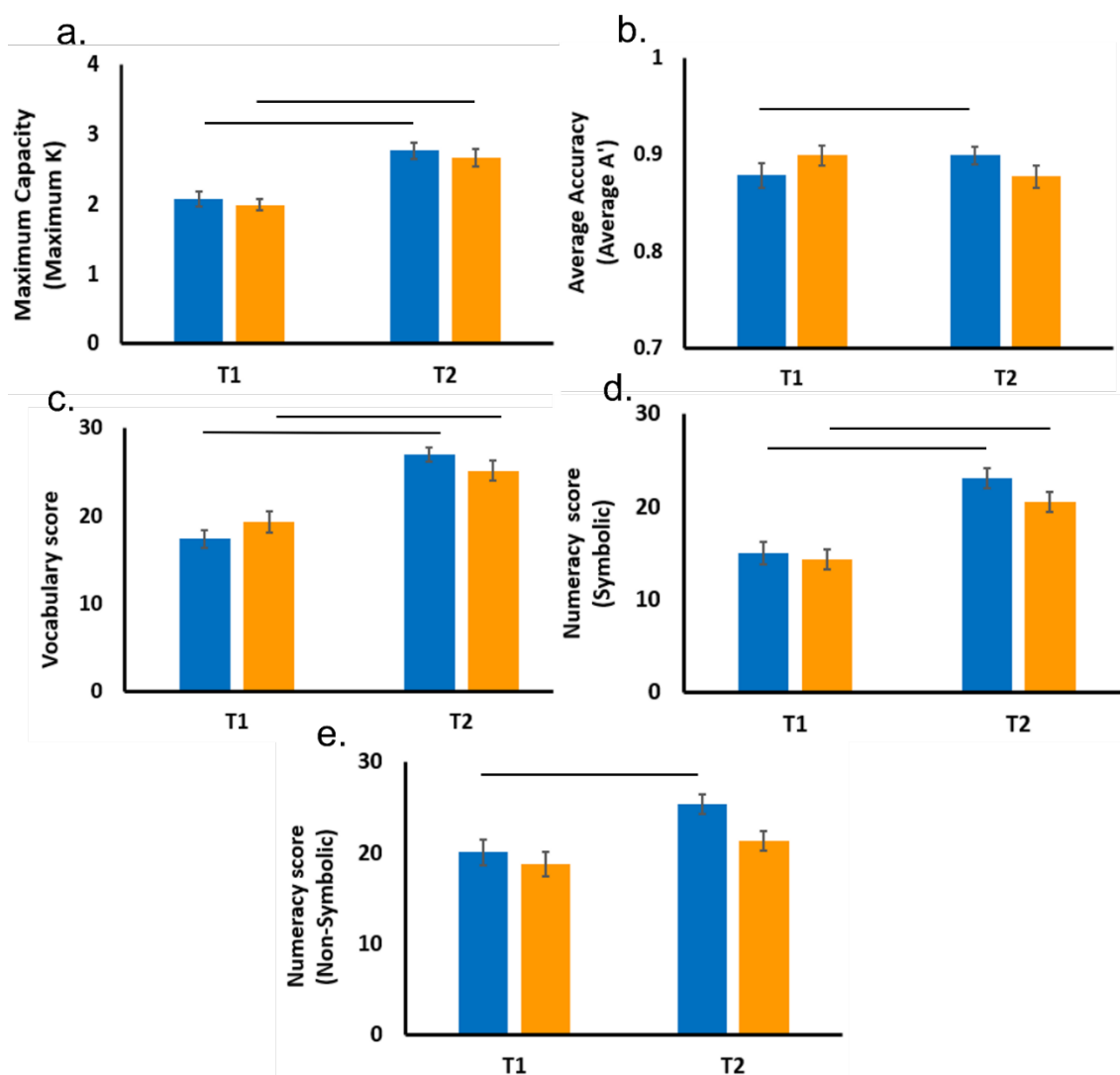
Figure 12. Bar plots showing **(a)** maximum K estimates **(b)** average A' estimates **(c)** vocabulary estimates **(d)** symbolic numeracy estimates and **(e)** non-symbolic numeracy estimates. P1 children shown in blue and KG children shown in orange. Error bars show SEM. '-' indicates significance at *p*<.05.

3.4.2 fNIRS results

The fNIRS data were comprised of HbO and HbR values for each of the 14 channels. To reduce data dimension and focus subsequent analysis only on effects that had a difference between HbO and HbR, initial repeated measure ANOVAs including chromophore (HbO, HbR) as a factor were run for each channel. The Benjamini-Hochberg test was run with a false discovery rate of 0.05 to control for the number of channels that were included in the analyses.

First, in line with Chapter 2, a difference measure was calculated to accompany the maximum K estimates. Specifically, activation at the low load was subtracted from activation at the high load and averaged across trial type at each timepoint. Thus, a repeated measures ANOVA with a within-subject factor of timepoint (T1, T2) and chromophore (HbO, HbR) and a between-subjects factor of group (P1, KG) was run on the difference in activation between the high load and the low load for each of the 14 channels. Second, to accompany average A' estimates, children's brain activation was collapsed across load and trial type at each timepoint. Thus, a repeated measures ANOVA with a within-subject factor timepoint (T1, T2) and chromophore (HbO, HbR) and a between-subjects factor of group (P1, KG) was run on children's average activation for each of the 14 channels. Significant interactions involving chromophore as a factor were followed up with post-hoc analyses conducted on the HbO estimates.

Difference in activation. Only channels that showed a significant interaction involving chromophore and that survived the Benjamini-Hochberg correction are reported. No significant interactions between time and chromophore or time, group, and chromophore were found.

Average activation. Only channels that showed a significant interaction involving chromophore and that survived the Benjamini-Hochberg correction are reported. A significant interaction between time and chromophore was found in the right middle frontal gyrus ($F[1,71] = 9.389$, $p=.003$). Post-hoc tests revealed activation at T2 was greater than activation at T1 ($p=.008$). No significant interactions between time, group, and chromophore were found.

3.4.3 Bivariate LCS modelling

To test whether average A', which showed a diverging pattern of change in the two groups, could predict academic achievement, the longitudinal coupling between average A' and performance on the academic tasks was investigated. Focus is placed on the bivariate relationships for P1 children only (since they showed an increase in average A' after one year of schooling) to determine whether the schooling-specific longitudinal changes in average A' could predict academic achievement.

Average A' and Academic Achievement. Bivariate longitudinal models were fitted for average A' and (1) vocabulary scores (2) math pack and (3) phonemes pack. Average A' at T1 predicted the change in vocabulary from T1 to T2. To follow up on this finding, the coupling pathway was constrained to be zero which led to a significant drop in model fit Δx^2 = 9.826, Δdf = 1, p = .002. Thus, average A' at T1 predicted the change in vocabulary from T1 to T2, suggesting that children who started out with better accuracy in VWM processing showed greater improvement in vocabulary scores after one year of schooling. Critically, vocabulary at T1 did not predict the change in average A'. Parameter estimates for P1 children are shown in Table 4. The change in average A' was positively correlated with math pack scores at T2 (p=.03). To follow up on this finding, the coupling pathway was constrained to be zero which led to a trend drop in model fit Δx^2 = 3.511, Δdf = 1, p = .061. Finally, average A' at T1 positively predicted phoneme scores at T2 (p=.032). To follow up on this finding, the coupling pathway was constrained to be zero which led to a trend drop in model fit Δx^2 = 3.673, Δdf = 1, p = .055.

Table 4. Bivariate couplings between average A' and vocabulary for P1 children. Standard errors are in parentheses. [*] Asterisks denote significance at *p* <.05 level.

Bivariate Couplings	
Intercept covariance ρ_{X1X2}	.06 (.06)
Average A' onto vocabulary change $Y1_{X2\Delta X1}$	34.58* (13.95)
Vocabulary onto average A' $Y2_{X1\Delta X2}$	0 (0)
Change-change covariance $\rho_{\Delta X1\Delta X2}$	0 (.03)

3.5 Discussion

The current study is the first neuroscientific investigation into the development of VWM and its neural correlates during the first year of formal schooling, and how this relates to academic achievement. VWM is an essential cognitive construct with strong links to academic success (Alloway & Alloway, 2010; Bull & Scerif, 2001; Gathercole, Pickering, Knight, et al., 2004; Swanson & Beebe-Frankenberger, 2004), making it an important system to understand in relation to early schooling. Here, measurements were collected across two years in two groups of children with little variation in birthdate. At T1, all children were 4.5-years-old and neither group had attended formal schooling. At T2, all children were 5.5-years-old and one group (P1) had completed 1 full year of schooling while the other group (KG) had stayed in kindergarten. Brain and behavioural data were collected on children while they completed a colour change-detection task in their homes. Academic achievement was also measured by examining performance on tasks assessing vocabulary and numeracy as well. Further, school achievement packs were included as school outcome measures to

assess how much P1 children learned across the school year. Critically, the present study aimed to determine whether there were any neurocognitive differences in VWM between these two groups of children, and to determine whether these differences were related to academic achievement. To investigate these relationships, latent change score models, a specific type of longitudinal SEM that are ideally suited to test developmental hypotheses were employed (Kievit et al., 2018).

Does one year of formal schooling lead to improvements in VWM processing and academic measures?

The current study used of a modified cut-off design to investigate the causal impacts of schooling. While traditional cut-off designs compare children born several months before and several months after an arbitrary date (leading to random group assignment), the current study took advantage of school commencement regulations in Scotland, where parents of children born in January and February each year can chose to enrol or defer their child's entry to school. Given that the decision to enrol lies with the parent, one might assume parents make this decision based on certain child characteristics, leading to fundamental differences between children who are enroled versus those who are deferred. However, the results of the current study suggest this is not the case. First, P1 and KG children showed no differences in performance at the first timepoint on either the cognitive or academic measures included here. Second, comparisons were made between enroled vs deferred children on a battery of parental questionnaires measuring child temperament, quality of the parent-child relationship, and a range of environmental factors including SES, level of disorganisation in the home, and number of daily hassles experienced by parents. In sum, these findings suggest parental beliefs concerning school readiness are not reflected in quantitative measures of cognitive function, academic performance, and child temperament included here. Nevertheless, it is still possible that the P1 and KG children were different in ways not measured here. For instance, although the questionnaires included

in the current study measured parenting behaviours, they did not provide an in-depth assessment of parental personality traits. Future research should collect more detailed information on parental characteristics to determine whether this might influence the decision to enrol or defer, and consequently, lead to differences between the two groups of children.

As predicted, P1 children made significantly greater improvements in VWM across the year than KG children. Importantly, there were no group differences in VWM at T1, suggesting the difference between the groups only emerged after exposure to formal schooling. These findings are supported by Zhang and colleagues (2019), who investigated whether interventions specifically targeting WM and IC could achieve comparable effects with schooling. The authors compared first grade children to age-matched kindergartners that were assigned to either a control group, a WM intervention group, or an IC intervention group. Children's WM and IC skills were tested before and after a 5-week intervention period, as well as during a follow-up three months later. For the WM task, no differences were found between the three groups at pre-test. However, at follow-up, they found that the schooling group and both intervention groups outperformed the control group. Thus, the authors concluded that both schooling and targeted intervention training have a similar and positive effect on WM skills. Further support stems from a study conducted by Finch (2019) who found WM skills grew more during the school months than the summer months, suggesting that school environments provide children with unique opportunities to improve their WM skills. Factors such as remembering specific class rules, following lengthy instructions, and engaging with challenging academic materials all place a demand on children's WM (Alloway et al., 2009; Peng et al., 2016). Thus, these findings suggest the school environment provided P1 children with greater opportunities to improve their VWM skills.

The present study further hypothesised that P1 children would show larger improvements than KG children in academic measures. Interestingly, this hypothesis was only supported for vocabulary. While literacy has been the focus of much schooling-related research, the findings have been somewhat

mixed. A recent review of the literature suggests schooling-related effects in literacy differ in magnitude depending on the type of literacy skill examined (Morrison et al., 2019). For instance, Kim and Morrison (2018) found decoding skills were predicted by pre-kindergarten, kindergarten, and first-grade schooling while reading comprehension was predicted by kindergarten and first-grade schooling. On the other hand, no schooling-related effects emerged for expressive vocabulary or sound awareness. This contrasts the findings of the current study, which found a positive effect of schooling on a test of expressive vocabulary. A potential reason for this discrepancy might be related to family SES status. While it is well documented that children's opportunities for home-based vocabulary learning varies by SES status (Hart & Risley, 1995), recent work conducted by Wright and Neuman (2014) additionally found SES differences in school-based vocabulary learning opportunities. Specifically, the authors found teachers from economically disadvantaged schools were less likely to discuss word meanings with children and also explained fewer challenging words. Consequently, this resulted in children from lower income schools receiving only 60% of the vocabulary instruction provided to their more economically advantaged peers. This is important, as several studies have demonstrated that instruction aids children's vocabulary acquisition (Kim, 2017). Biemiller and Boote (2006) reported that high-intensity instruction (e.g., in-depth discussion) could facilitate the learning of around 42% of taught words and that low-intensity instruction (e.g., giving definitions) could facilitate a further 22%. Thus, given that the overwhelming majority of P1 children in the current study were from high SES homes, it is likely they were enroled into economically advantaged schools that provided a greater degree of instructional learning, leading to an improvement in vocabulary.

In line with findings from Chapter 2, KG children (who performed more poorly than P1 children on the VWM task) were expected to show more dramatic modulation in activation in the frontal and parietal regions, however, this was not the case. Several reasons for this discrepancy are discussed. First, a behavioural estimate such as accuracy is a culminative measure that is the result of several underlying brain processes. Thus, while these neural

processes work together to produce significant behavioural change, it might be that the channel-based analysis approach used here was not sensitive enough to pick up on these smaller changes in clusters of voxels. One way to improve upon this would be to conduct more specific analyses. For instance, image reconstruction is an alternative analysis method that uses a head model to generate functional images from the fNIRS data, transforming surface level channel-based data into a volumetric representation within the brain (Forbes et al., 2021). Another limitation may be related to the type of fNIRS system used here, which included eight sources and eight detectors. Thus, it might be that the number of optodes was not sufficient to adequately cover the regions that were actively changing. However, this is unlikely given that the probe geometry was carefully designed based on ROIs from previous fMRI and fNIRS literature. Lastly, a potential challenge when collecting longitudinal fNIRS brain data is ensuring the recorded area stays consistent over time. This is particularly challenging in development when children's brains are continuously developing and growing. However, recent work by Collins-Jones et al. (2021) used image reconstruction to investigate the effects of variation in array position and head size in channel-space analysis of longitudinal fNIRS infant data. They found that the inferences drawn from group level channel-based analysis are unlikely to be significantly affected by variability in array position and shifting head sizes, though this effect is more pronounced at the individual level. Further, the present study took several measures to limit the possibility that shifting head sizes would interfere with the recordings. For instance, during each testing session the child's head circumference was measured in order to select the appropriately sized cap. Further, specific measurements were taken to ensure the cap was centred on the head in a standardized way.

Is there an association between VWM abilities and academic achievements after one year of formal schooling?

Results indicated that P1 children who began the year with better VWM gained more in vocabulary across the school year. One interpretation for this finding is

related to the context of the schooling environment. Specifically, schooling is a learning context that places a heavy demand on children's VWM skills. In other words, "learning" itself depends on VWM. Thus, children who begin the year with better VWM are able to learn more in this schooling context, and consequently, show greater improvements in vocabulary across the year. While Nevo and Bar-Kochva (2015) did not examine this relationship in the context of the schooling environment, they did investigate the predictive effects of early WM abilities to developing reading skills and found similar results. Specifically, these researchers tested VWM in kindergarten and reading skills in grades 1, 2, and 5. They found that visual-spatial memory predicted reading comprehension in grades 2 and 5, alluding to a long-lasting role of early VWM as a predictor of variance in reading. Why might VWM predict subsequent reading and/or language abilities? Clerkin et al. (2017) reported that the number of times an object is seen, rather than how many times the object-word is heard, predicted what words infants learn first. Thus, the accumulation of word knowledge might be directly related to the development of visual processing in object-name learning. Further, a developmental relationship between memory and word learning has been reported for cross-situational word learning, a technique for learning words across multiple exposures despite uncertainty of the word's meaning on each exposure. Specifically, Vlach and DeBrock (2017) examined relations between age, recognition memory abilities, language abilities, and cross-situational word learning performance in 2- to 5-year-old children. They found that recognition memory abilities were the strongest predictor of cross situational word learning performance, above and beyond age and other cognitive abilities. The authors proposed that in order to successfully learn a word, children must encode, retain and retrieve a large amount of information. Specifically, children must remember visual information (objects they see) and auditory information (words they hear) and bind the two together in time. Following on from this research, Bhat and colleagues (2020) developed a computation model with fields for word-object mapping, visual attention, and memory to simulate developmental changes in memory retention. By varying the decay parameters, which represented the forgetting of correct information, they found the same trend as reported by Vlach and DeBrock (2017),

confirming that developmental changes in the memory system play a critical role in children's word learning.

Interestingly, a similar pattern of results emerged for phonetic awareness. Although this finding did not survive the formal model comparison, VWM abilities at the start of the year showed a positive trend with scores on the phonemes pack. Based on previous research that has shown an association between children's vocabulary and phonetic awareness skills (McDowell et al., 2007; Whitehurst & Lonigan, 2001) it is conceivable that better VWM may play a role in predicting phonetic awareness as well as vocabulary. In addition, the change in VWM showed a positive trend with math pack scores at T2, suggesting that P1 children who improved more in VWM also performed better in a math assessment. This finding is in line with several previous studies that found a positive association between VWM abilities and numeracy skills (Alloway & Alloway, 2010; R. Bull & Scerif, 2001). However, this finding also did not survive the formal model comparison and thus, the relationships between VWM and the school achievement packs must be interpreted with caution and necessitate replication tests.

The current study employed a modified cut-off design to investigate the causal impact of one year of schooling on children's academic achievements and VWM function. One year of schooling resulted in an improvement in vocabulary and VWM performance highlighting the importance of factors such as exposure to a structured learning environment, instructional quality and interactions with teachers and peers. Further, due to the nature of the schooling environment, children who begin the year with better VWM make greater improvements in vocabulary. Taken together, these findings indicate exposure to formal schooling not only improves cognitive function but has important implications for subsequent academic success.

CHAPTER 4 NEURAL NETWORK UNDERLYING RESPONSE INHIBITION IN PRE-SCHOOLERS VARIES ACCORDING TO PERFORMANCE

4.1 Abstract

IC is an essential cognitive skill involved in controlling one's thoughts, behaviours, attention, and emotions in order to inhibit a dominant or prepotent response in favour of a more appropriate one, given particular context. IC has important implications for multiple aspects of development including academic achievement and psychosocial outcomes. The objective of the current study was to investigate individual differences in response inhibition and its neural correlates and relate these differences to temperamental and environmental factors. Specifically, the present study collected behavioural data in response to a go/no-go task and brain activation data (using fNIRS) in a sample of 4.5-year-old children in their homes. Parents were asked to fill in questionnaires assessing the child's temperament and aspects of their home environment. Children were median split into HP and LP groups based on go/no-go task performance. Results showed LPs showed a greater difference in activation between go and no-go trials than HPs in channels overlying the right frontal cortex, the left frontal cortex, the right parietal cortex, and the left parietal cortex. These findings suggest LPs recruited these regions to a greater extent than HPs due to the increased strain on their inhibitor processes. Correlational analyses were run to examine the association between the difference in activation between go and no-go trials and variables from the parental questionnaires, but no significant relationships emerged. These findings suggest that while lower performance on a go/no-go task is related to larger recruitment of the frontal and parietal regions in young children, this is not related to the temperamental and environmental factors measured here.

4.2 Introduction

IC refers to the ability to control one's thoughts, behaviours, attention, and emotions in order to inhibit a dominant or prepotent response in favour of a more appropriate one, given particular context (Diamond, 2013). IC is an essential cognitive skill that has important implications for multiple aspects of development. Converging evidence has linked early IC to future academic achievement (Blair & Razza, 2007; Gawrilow et al., 2014; McClelland et al., 2014; Smith-Donald et al., 2007; Son et al., 2019) and psychosocial outcomes (Anzman-Frasca et al., 2015; Eisenberg et al., 2001; Rhoades et al., 2009; Shoda et al., 1990).

Several tasks have been developed to assess IC across development. Tasks measuring simple response inhibition often involve withholding or delaying a pre-dominant response and have been effectively used to measure inhibition even in infants (Kochanska et al., 1996, 1998). Examples include "don't" paradigms where toddlers must supress a rewarding behaviour and "delay" paradigms where they must delay gratification (Garon et al., 2008). When children reach the pre-school period, inhibition tasks become more complex and often place additional demands on WM. These tasks generally require children to hold a rule in mind and respond according to this rule, while simultaneously inhibiting a prepotent response (Garon et al., 2008). Studies employing complex inhibition tasks have generally found age-related improvements in response inhibition between the ages of 3 and 5 (see Garon et al. (2008) for a review). One such task is the go/no-go task used in this investigation, where children must respond to the presence of a target stimulus (go trials) and supress a response in the presence of a non-target stimulus (no-go trials). Go/no-go tasks have been extensively used to assess the development of inhibition, with previous research consistently reporting greater accuracy for go trials than for no-go trials (Brocki & Bohlin, 2004; Jonkman, 2006; Lewis et al., 2017). While inhibition continues to improve in middle childhood, Best and Miller (2010) argue these improvements do not reflect fundamental changes in cognition, but rather, refinements involving quantitative

improvements in accuracy and increasing efficiency in overriding a prepotent response. A potential way to gain further insight into these more subtle refinements is through the use of neuroimaging techniques.

In the adult neuroimaging literature, regions that are more extensively activated in response to no-go trials than to go trials are thought to specifically reflect response inhibition, while regions that are similarly activated during both trial types may reflect decision formation and monitoring that is required for both types of trials (Liddle et al., 2001). Several adult fMRI studies have reported that activation in the dorso-lateral PFC, anterior insula, and bilateral parietal cortex is more active during no-go trials than go trials, suggesting these regions are specifically implicated in response inhibition (Dodds et al., 2011; Kelly et al., 2004; Liddle et al., 2001; Rubia et al., 2001; Smith et al., 1998). Given the challenges associated with collecting fMRI data on young children, many neurodevelopmental investigations into response inhibition have been conducted using EEG. In the adult ERP literature, two main electrophysiological components are thought to be related to response inhibition: the N2 and the P3. The N2 is a negative deflection over the frontocentral regions and is consistently found to be more robust in response to no-go than to go trials (Cheng et al., 2019). The P3, a positive deflection, can be observed in the parietal region in response to go trials and the frontocentral regions in response to no-go trials (Cheng et al., 2019). Hoyniak (2017) conducted a meta-analysis of 65 studies that assessed response inhibition in children aged 2 to 12 using the go/no-go task and found that the N2 was larger in response to no-go trials than to go trials and decreased in amplitude / latency across childhood. Durston et al. (2002) conducted an fMRI study on a sample of children aged 6 to 10 and adults and found similar results. Both children and adults showed greater activation for no-go trials compared to go trials in the bilateral ventral PFC, the right dlPFC, and the right parietal lobe. Further, the magnitude of this difference was greater for children than for adults suggesting that although children recruited the same neural circuitry as adults, they did so less efficiently by activating these regions to a greater extent. This was supported by Mehnert et al. (2013) who used fNIRS to compare activation in children aged 4 to 6 and

adults during a go/no-go task. They found both groups showed an increase in activation in response to no-go trials than to go trials, with children showing greater activation than adults for both trial types.

Contradicting this research, an fMRI study conducted by Bunge et al. (2002) examined response inhibition in children aged 8 to 12 and adults. When comparing activation for no-go trials versus go trials, they found adults activated several frontal and posterior brain regions implicated in response inhibition, however, in children, no clusters survived the statistical threshold. At a more lenient threshold, small foci in the frontal gyrus were activated, suggesting children may only recruit a subset of the adult circuitry. Another fMRI study conducted by Brod and colleagues (2017) assessed IC in 5- and 6-year-old children, before and after one school year. They found no differences in activation between go trials and no-go trials at either timepoint. These researchers employed a more challenging version of the go/no-go task where several different go and no-go stimuli were included. Thus, the authors concluded that, due to the additional strain on WM, children may have found both go trials and no-go trials challenging, and therefore did not exhibit differences in activation according to trial type.

The findings highlighted above provide valuable insight into the development of inhibitory skills, however, children vary considerably in their inhibitory capacity (Carlson & Wang, 2007; Troller-Renfree et al., 2019). Characterising these individual differences could provide further insight into the development of response inhibition and potentially identify those who may be at risk for developmental disorders. For instance, previous research has found that deficits in response inhibition are implicated in behavioural disorders in childhood such as ADHD (Berlin et al., 2003). Researchers have also linked inhibition in childhood to certain behaviours and temperaments. Specifically, Wolfe and Bell (2004) administered two tasks assessing WM and IC to a sample of 4.5-year-old children. They found performance on these tasks was positively associated with two of the four subscales that compromise the effortful control factor of the Children's Behavioural Questionnaire. More specifically, performance was positively associated with attention focusing and

inhibitory control but not with low sensitivity pleasure and perceptual sensitivity. The authors argued the association only existed for attention focusing and inhibitory control as these two subscales draw more heavily on the cognitive component of the effortful control factor. Additionally, a negative correlation was found between performance and the anger / frustration scale, consistent with previous research in toddlers that found those who performed better on an EF task were also more able to regulate their anger and frustration (Gerardi-Caulton, 2000).

In addition to internal factors, variations in children's home environments have also been linked to the development of inhibition. The home environment is an umbrella term used to describe a set of variables relating to the environment a child is reared in. Thus, the home environment can include aspects of the child's physical environment, as well as social factors such as the quality of the parent-child relationship (Leventhal & Brooks-Gunn, 2001). Bosquet Enlow et al. (2019) examined the role of maternal and child lifetime stress, maternal caregiving in infancy and early childhood, and infant temperament on WM and IC. Maternal demographics were collected during pregnancy and infant temperament was assessed when children were 6-months old. In addition, when children were 3.5-years-old, they completed a go/no-go task assessing inhibition while mothers completed a questionnaire on exposure to stressors since pregnancy. The authors found poorer IC was associated with greater maternal lifetime exposure to stress / trauma during pregnancy, but not with maternal or child lifetime exposure to stress / trauma. Further, greater IC was associated with more emotionally supportive maternal behaviour during infancy and greater cognitive stimulation in childhood. Another environmental factor that has been extensively studied in the developmental literature is SES. Specifically, several studies have reported poorer IC skills in children from lower SES backgrounds (Hassan et al., 2019; Sarsour et al., 2011; St. John, Finch, et al., 2019; St. John, Kibbe, et al., 2019; Xing et al., 2019).

Based on the review above, several questions remain that need to be addressed. Specifically, it is unclear whether children (who consistently show

poorer behavioural performance than adults) consequently recruit the frontal and parietal regions to a greater extent (and show large activation differences between go and no-go trials) or to a lesser extent (and show reduced or no activation differences between go and no-go trials). To help explain these contradictory findings, the current study aimed to determine whether further insight into the neural pathways underlying response inhibition in children could be gained by examining *performance differences*, and to relate these differences to the temperamental and environmental factors identified in the literature. The present study collected fNIRS data on a sample of 4.5-year-old children with little variation in birth date while they completed a go/no-go task in their homes. No study to date has yet examined the neural networks underlying performance differences in pre-schooler's IC in a home-setting. Although laboratory testing allows for experiments to be conducted under strictly controlled conditions, in doing so, children are tested in an artificial and stressful environment. A primary advantage of home testing is children are provided the opportunity to perform the task in a relaxed environment, which also increases the ecological validity of the paradigm. The present investigation employed the task as described by Brod et al. (2017). Based on previous behavioural findings reported in the developmental literature (Booth et al., 2003; Brod et al., 2017; Bunge et al., 2002), it is hypothesized that children will show greater accuracy for go trials than for no-go trials. Predictions for performance differences in brain activation stem from previous findings that compare brain activation in adults and children and relate poorer behavioural performance in children to increased recruitment of frontal and parietal areas (Durston et al., 2002; Mehnert et al., 2013). Thus, it is expected LPs (who perform worse on the task) will recruit the frontal and parietal regions to a greater extent than HPs.

4.3 Methods

4.3.1 Participants

Ninety-five 4.5-year-olds (45 females, *Mage* = 53.5 months, *SD* = 1.2) participated in the research. Additionally, one of the parents of each child also took part by filling out a series of questionnaires. More detailed participant information and criteria for inclusion can be found in Chapter 2 (section 2.3.1).

Data from 29 children had to be excluded from analyses for varying reasons; eleven children refused to wear the fNIRS cap, two children had thick hair that prevented contact between the optodes and the scalp, and data from another two children was lost due to experimenter error. A further 14 participants were removed for contributing fewer than seven usable correct no-go trials. A total of 66 children (36 females, *Mage* = 53.5 months, *SD* = 1.2) contributed to the final analyses.

Parental educational attainment was high for both the HP and LP groups. Specifically, 100% of HP children and 88% of LP children had at least one parent who attained a BSc degree or higher. In 2018 the average household disposable income in the UK was £34,200 (Office for National Statistics, 2019). The net annual household income was higher than the national average for both the HP group (*M* = 7 (category £60,000 – 70,000), *SD* = 2) and the LP group (*M* = 7 (category £60,000 – 70,000), *SD* = 3), and the groups did not differ significantly *t*(63)= .063, *p* =.95.

4.3.2 Experimental task

The cats-and-dogs task (CDT) as described by (Brod et al., 2017) was used to measure IC in children – see Figure 13. The task was run in E-prime V.3 software on a HP laptop with a 14-inch screen. During "go" trials, children saw a picture of a dog and were supposed to press a button (spacebar). During "no-go" trials, children saw a picture of a cat and were supposed to withhold pressing a button. To ensure children understood the rules, the session began with a practice consisting of 3 blocks. The first block contained 6 pictures (4 dogs, 2 cats) that remained on the screen until the child made the appropriate response. The second block contained 6 pictures (4 dogs, 2 cats) that were timed at 1 second. The third block contained 10 pictures (8 dogs, 2 cats) that

were timed at 500ms. During the practice, children were reminded of the rules if they made a mistake. After children completed all practice blocks, the test session began. The test session was split into two runs. The first run was comprised of 59 trials: 44 go trials and 15 no-go trials. Run 2 was comprised of 69 trials: 52 go trials and 17 no-go trials. Pictures of cats and dogs were presented for 500ms, followed by a fixation cross as jitter that ranged in duration from 2 to 8 seconds. Responses made during stimuli presentation or during the fixation cross period were recorded. Go trials were presented 3 times as often as no-go trials. The order of presentation of go and no-go trials was pseudorandom, with the constraint that no-go trials were preceded equally often by 1, 2, 4 or 5 go trials.
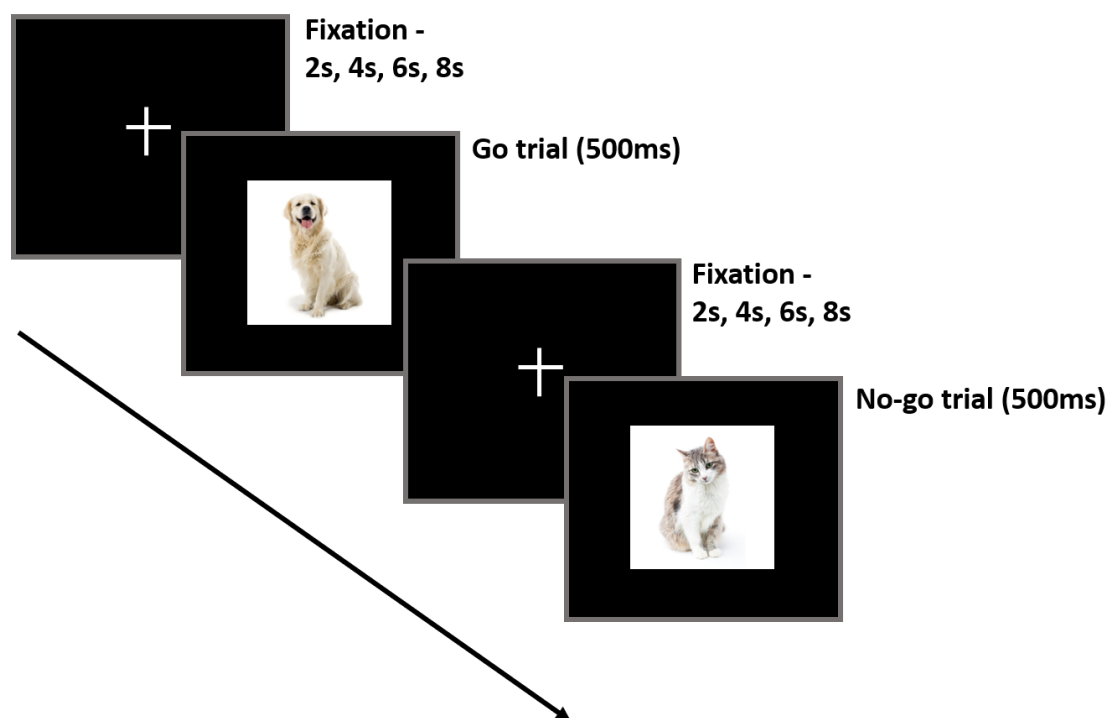
Figure 13. Trial structure of the Cats-and-Dogs Task (CDT).

4.3.3 fNIRS data acquisition

fNIRS data were collected at 7.81 Hz using a NIRSport system 8x8 (8 sources 8 detectors) / release 2.01 with wavelengths of 850 and 760 nm. Fiber optic cables carried light from the machine to a NIRS cap. Probe geometry was designed by collating regions of interest (ROI) from previous fNIRS and fMRI literature (Brod et al., 2017; Wijeakumar et al., 2015). Probe geometry consisted of four channels each on the left and right frontal cortices, and three channels each on the left and right parietal cortices (see Figure 2). Note that short-source-detector channels were not used to regress scalp hemodynamics as all the channels were directed toward maximising coverage of the frontal and parietal cortices. Four cap sizes (50cm, 52cm, 54cm, and 56cm) were used to accommodate different head sizes. Source-detector separation was scaled according to cap size (50cm cap: 2.5cm; 52cm cap: 2.6cm; 54cm cap: 2.7cm and 56cm cap: 2.8cm). To synchronise behavioural and fNIRS data, a McDaq data acquisition device (www.mccdaq.com) was used to send information from the task presentation laptop to the fNIRS system.

4.3.4 Procedure

For more details on the general set-up, refer to Chapter 2 (section 2.3.4) . Once the equipment was safely positioned, the experimenter began the session by telling children they would be playing several games. The order of the tasks was counterbalanced, with half of the children receiving the colour change-detection task first (described in Chapter 2), and the other half receiving the CDT first (described here). The experimenter began the practice session by introducing the task as the cats-and-dogs game and displaying the instructions screen. To familiarise the children with the images, the instructions screen contained the 6 pictures (2 cats, 4 dogs) to be used during the practice. At the start of the first practice block, children were told, "In this game you will see these pictures of cats and dogs and you need to push this button (spacebar) when you see one of the dogs, so we can take it for a walk! You must not push the button when you see one of the cats, because we can't take cats for a

walk." At the start of the second practice block, children were reminded of the rules and told, "This time the picture are going to come up fast, so when you see a dog, try push the button as fast as you can!". Before the final practice block, children were told the pictures would appear even faster. The instructions were briefly repeated at the start of each test run. To keep children engaged, each test run contained different pictures of cats and dogs. To maintain motivation, children were also rewarded with a sticker after each run.

4.3.5   Parental questionnaires

While children completed the task, parents were given a booklet of questionnaires to complete. Variables from these questionnaires have previously been shown to be associated with cognitive function in children (see Chapter 2 - section 2.3.5). The booklet included the Strengths and Difficulties Questionnaire (Goodman, 1997), the Parenting Daily Hassles scale (Crnic & Booth, 1991; Crnic & Greenberg, 1990), The Confusion, Order and Hubbub Scale (Matheny et al., 1995), the Parenting Stress Index (Abidin et al., 2013) and a socio-economic scale that assessed income, education and parental aspirations.

4.3.6   Behavioural analyses

Accuracy was calculated separately for each trial type (go and no-go) and test run (run 1 and run 2). Median reaction time was calculated for correct go trials. Seventeen children completed only run 1, two children completed only run 2, and 47 children completed both run 1 and run 2. A weighted average of accuracy ad RT was calculated to account for the difference number of trials included in each run.

$$\text{Weighted average}= \frac{\big((\text{run 1 score} * \text{run1 number of trials})+(\text{run 2 score} * \text{run 2 number of trials})\big)}{\text{Total number of trials}}$$

After computing the weighted averages, a corrected measure of accuracy was additionally calculated for each subject by subtracting no-go incorrect responses from go correct responses ($Go_{correct}$-$NoGo_{incorrect}$). This measure was calculated as it captures how accurately children performed on both go and no-go trials. Lastly, a median-split was applied to the $Go_{correct}$-$NoGo_{incorrect}$ values to divide participants into two performance groups: LPs and HPs. $Go_{correct}$-$NoGo_{incorrect}$ estimates were used for this categorization as this measure is the most accurate representation of how well children performed on the task.

4.3.7 Pre-processing fNIRS signals

fNIRS data were pre-processed using the Homer2 package (https://www.nitrc.org/projects/homer2/). Raw data were pruned using the *enPrunechannels* function (SNRthresh=2, SDrange=0.0 – 45). Signals were converted from intensity values to optical density (OD) units using the *Intensity2OD* function. Data was corrected for motion using the *hmrMotionCorrectPCArecurse* function, (tMotion=1, tMask=1, STDEVthresh=50, AMPthresh=0.5, nSV=0.97, maxIter=5, turnon=1). Data was scanned for motion artifacts using *hmrMotionArtifactByChannel* function (tMotion=1, tMask=1, STDEVthresh=50, AMPthresh=0.5). Then, the function *enStimRejection* (tRange=-1 to 3) was used to turn off stimulus triggers that contained motion artifacts. The data were band-pass filtered using *hmrBandpassFilt* to include frequencies between 0.016Hz and 0.5Hz. Using the function *hmrOD2Conc*, the OD units were converted to concentration units. To find trials that were outliers with respect to the average HRF, we used the function *hmrFindHrfOutlier* (tRange=-1 to 3, STDEVthresh=3, minNtrials=3). Lastly, the HRF was estimated using the ordinary least squares method with a modified gamma function with a square wave (*hmrDeconvHRF_DriftSS* function [tRange=-1 to 3, paramsBasis=0.1,0.5,0.5, rhoSD_ssThresh=0, flagSSmethod=0, driftOrder=3, flagMotionCorrect=0]).

4.3.8   fNIRS group analyses

Only correct trials were included in the fNIRS group analyses. HbO and HbR beta values were extracted for each test run (run 1 and run 2) and each condition (go and no-go). A weighted average was calculated to account for the different number of trials included in each run to produce one beta estimate per subject (N=66), per condition. For run 1, the mean number of correct trials included for HPs was 37.5 ± 0.7 go trials and 12.4 ± 0.4 no-go trials and for LPs 34.1 ± 1.1 go trials and 8.7 ± 0.5 no-go trials. For run 2, the mean number of correct trials included for HPs was 43.9 ± 0.9 go trials and 14.2 ± 0.4 no-go trials and for LPs 38 ± 1.2 go trials and 8.9 ± 0.7 no-go trials.

A repeated measures ANOVA was run for each of the 14 channels. Each ANOVA included within-subject factors of trial type (go and no-go) and chromophore (HbO, HbR) and a between-subjects factor of group (HPs and LPs). Only effects that showed a significant interaction with chromophore were selected to ensure differences between HbO and HbR activation. Further, to determine how activation differed between the conditions, channels showing a significant interaction between trial type and chromophore were selected. Lastly, channels that showed a significant interaction between group, trial type and chromophore were examined to establish differences between HPs and LPs. The Benjamini-Hochberg test was run with a false discovery rate of 0.05 to control for the number of channels that were included in the analyses. To determine significant effects, individual p-values were compared to the critical Benjamini-Hochberg value. All channels with p-values for the interaction effect that were less than the critical value were considered significant. Lastly, Bonferroni correction was applied to the post-hoc tests conducted in following up these significant interactions. For more details on the Benjamini-Hochberg correction, refer to Chapter 2 (section 2.3.8).

4.3.9 Correlations between behaviour, brain function and parental questionnaire data

All questionnaire data were log-transformed to account for skewed distributions. The full dataset was screened for outliers that were 3 standard deviations above or below the mean. Nine outliers were identified and winsorized – two in the right frontal, one in the left frontal, four in the Strengths and Difficulties Questionnaire, and two in the parental education measure. Following outlier correction, we correlated our questionnaire variables with our behavioural and brain measure. The Benjamini-Hochberg test was run with a false discovery rate of 0.1 to control for the number of significance tests on correlations that were performed. All correlations with p-values less than the critical Benjamini-Hochberg value were considered significant.

4.4 Results

4.4.1 Behavioural results

Accuracy for go trials (M=0.85, SD=0.11) was greater than accuracy for no-go trials (M=0.7, SD=0.19, t[65] = 6.104, p<.001) – see Figure 14(a). A median split was applied to the $Go_{correct}$-$NoGo_{incorrect}$ values. The median $Go_{correct}$-$NoGo_{incorrect}$ estimate was 0.61. This resulted in a total of 33 HPs (18 females) and 33 LPs (18 females). Figure 14(b) shows the mean $Go_{correct}$-$NoGo_{incorrect}$ estimates for HPs (0.74 ± 0.02 items) and LPs (0.36 ± 0.03 items). An independent-samples t-test was conducted to compare reaction times between the HP and LP groups. During correct go trials, LP (M= 868.47, SD = 175.76) had significantly faster response times than HP (M= 1017.69, SD = 261.52), (t[65] = 2.720, p=.008). This suggests that LP might have the tendency to press the space bar too fast, leading to conducting more inappropriate presses during the no-go trials. This is reflected in the behavioural results, where HPs had an average of 90% correct for go trials and 85% correct for no-go trials, while LPs had an average of 80% correct for go trials and 56% correct for no-go trials – see Figure 15.
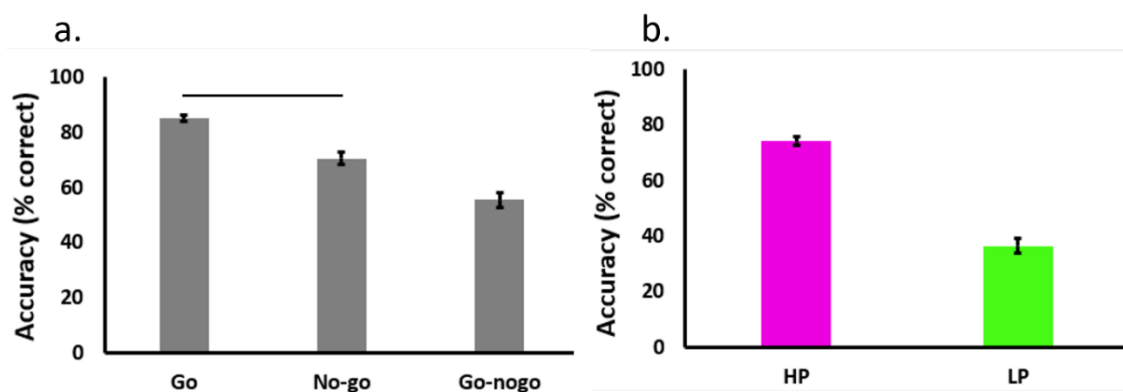
Figure 14. (a) Accuracy (% correct) for trial type (go and no-go) and $Go_{correct}$-$NoGo_{incorrect}$. **(b)** $Go_{correct}$-$NoGo_{incorrect}$ accuracy for high and low performers. Error bars show SEM. '-' indicates significance at $p<.05$.
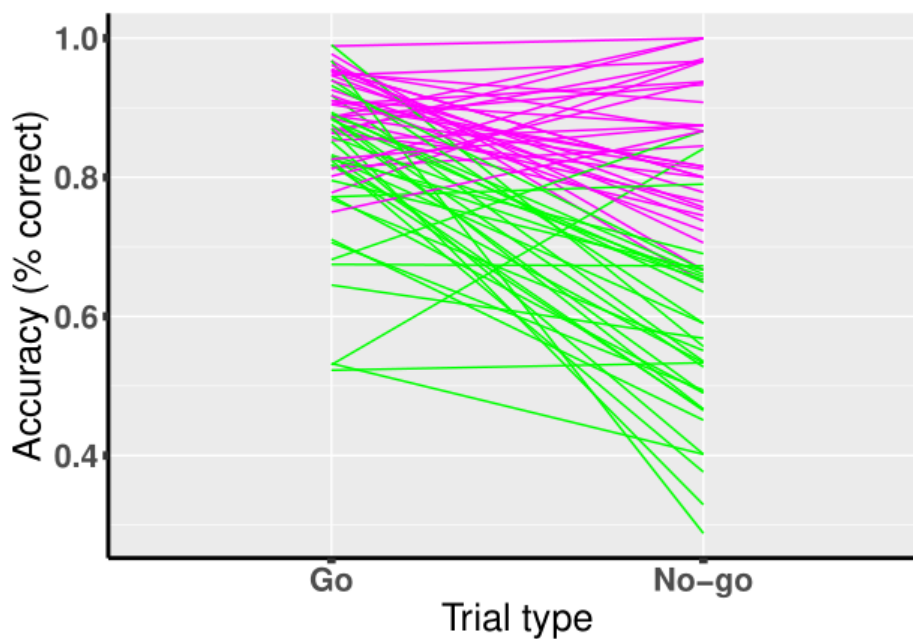
Figure 15. Spaghetti plot showing accuracy (% correct) according to trial type for LPs (green) and HPs (magenta).

4.4.2 fNIRS results

Table 5 displays the post-hoc effects for HbO activation for channels that showed a significant interaction between trial type and chromophore as well as group, trial type, and chromophore. See Appendix F, Table F1 for the post-hoc effects for HbR activation. Only effects in channels that survived the Benjamini-Hochberg correction are reported. Table 5 also shows the MNI label for the centre of mass of the brain areas underlying channels with significant effects. A significant interaction between trial type and chromophore was observed in channels overlying the left middle frontal gyrus (F[1,64] = 10.070, p=.002) and the left supramarginal gyrus (F[1,78] = 9.477, p=.003). Posthoc tests revealed that activation was greater for go trials than for no-go trials.

The interaction between group, trial type, and chromophore was significant in channels overlying the right middle frontal gyrus (F[1,64] = 5.059, p=.028), the right inferior frontal gyrus (F[1,64] = 6.853, p=.011; F[1,64] = 7.116, p=.01), the left middle frontal gyrus (F[1,64] = 7.410, p=.008; F[1,64] = 13.234, p=.001), the left inferior frontal gyrus (F[1,64] = 10.122, p=.002; F[1,64] = 8.062, p=.006), the right supramarginal gyrus (F[1,64] = 8.887, p=.004), the left inferior parietal lobule (F[1,64] = 10.844, p=.002), and the left supramarginal gyrus (F[1,64] = 12.414, p=.001). Posthoc tests revealed that in all these regions, LPs showed more negative activation for no-go trials than for go trials. Importantly, HPs did not show a difference in activation according to trial type. Further, in the right inferior frontal gyrus, left inferior frontal gyrus, right supramarginal gyrus, left inferior parietal lobule, and left supramarginal gyrus, LPs showed more negative activation than HPs during no-go trials.

Table 5. Channels showing significant interactions between trial type and chromophore, as well as between group, trial type and chromophore. Posthoc results are shown for HbO activation.

Channel No.	Brain areas (MNI coordinates)	Trial x Chromophore (HbO)	Group x Trial x Chromophore (HbO)
Channel 1	Right middle frontal gyrus		LP: Go > No-go (p = 0.014)
Channel 2	Right middle frontal gyrus		
Channel 3	Right inferior frontal gyrus		No-go: HP > LP (p = 0.026) LP: Go > No-go (p = 0.005)
Channel 4	Right inferior frontal gyrus		LP: Go > No-go (p = 0.013)
Channel 5	Left middle frontal gyrus		LP: Go > No-go (p = 0.006)
Channel 6	Left middle frontal gyrus	Go > No-go (p = 0.006)	LP: Go > No-go (p < 0.001)
Channel 7	Left inferior frontal gyrus		No-go: HP > LP (p = 0.005) LP: Go > No-go (p = 0.001)
Channel 8	Left inferior frontal gyrus		No-go: HP > LP (p = 0.01) LP: Go > No-go (p = 0.002)
Channel 9	Right angular gyrus		
Channel 10	Right superior occipital gyrus		
Channel 11	Right supramarginal gyrus		No-go: HP > LP (p = 0.002) LP: Go > No-go (p < 0.001)
Channel 12	Left inferior parietal lobule		No-go: HP > LP (p= 0.001) LP: Go > No-go (p = 0.004)
Channel 13	Left angular gyrus		
Channel 14	Left supramarginal gyrus	Go > No-go (p = 0.003)	No-go: HP > LP (p = 0.002) LP: Go > No-go (p < 0.001)

4.4.3 Correlations between behavioural performance, brain activation, and parental factors

The ANOVA revealed that the difference in activation between go trials and no-go trials across time differentiated HPs from LPs. To relate these neural differences in brain to behavioural and questionnaire data, an average difference in activation (go activation – no-go activation) was computed across channels that showed the significant 4-way interaction to create four brain clusters as they showed similar trends. The four brain clusters included the right frontal cortex (channel 1, channel 3, and channel 4 – see Figure 16(a), left frontal cortex (channel 5, channel 6, channel 7, and channel 8 – see Figure 16(b), right parietal cortex (channel 11 – see Figure 16(c) and left parietal cortex (channel 12 and channel 14 – see Figure 16(d). As expected, the difference in activation between trial type in the left frontal cortex, the right parietal cortex, and the left parietal cortex was negatively correlated with $Go_{correct}$-$NoGo_{incorrect}$ accuracy, suggesting that children who showed a greater difference in activation between trial type (LPs) performed worse on the task (see Figure 17).

Correlations were run between the difference measure in each brain region and data from the parental questionnaires. The Benjamini-Hochberg correction was applied with a false discovery rate of 0.1. No correlations survived the correction.
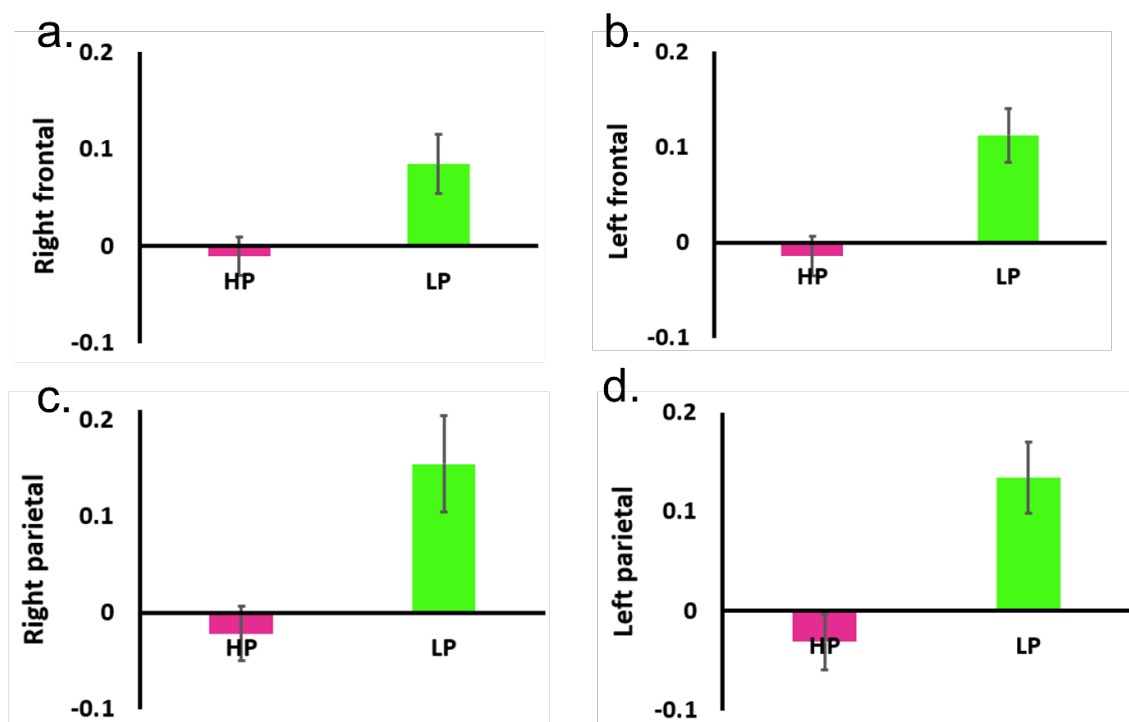
Figure 16. Bar plots showing the difference in HbO activation between go and no-go trials for HPs (magenta) and LPs (green) in the **(a)** right frontal **(b)** left frontal **(c)** right parietal and **(d)** left parietal. Error bars show SEM.
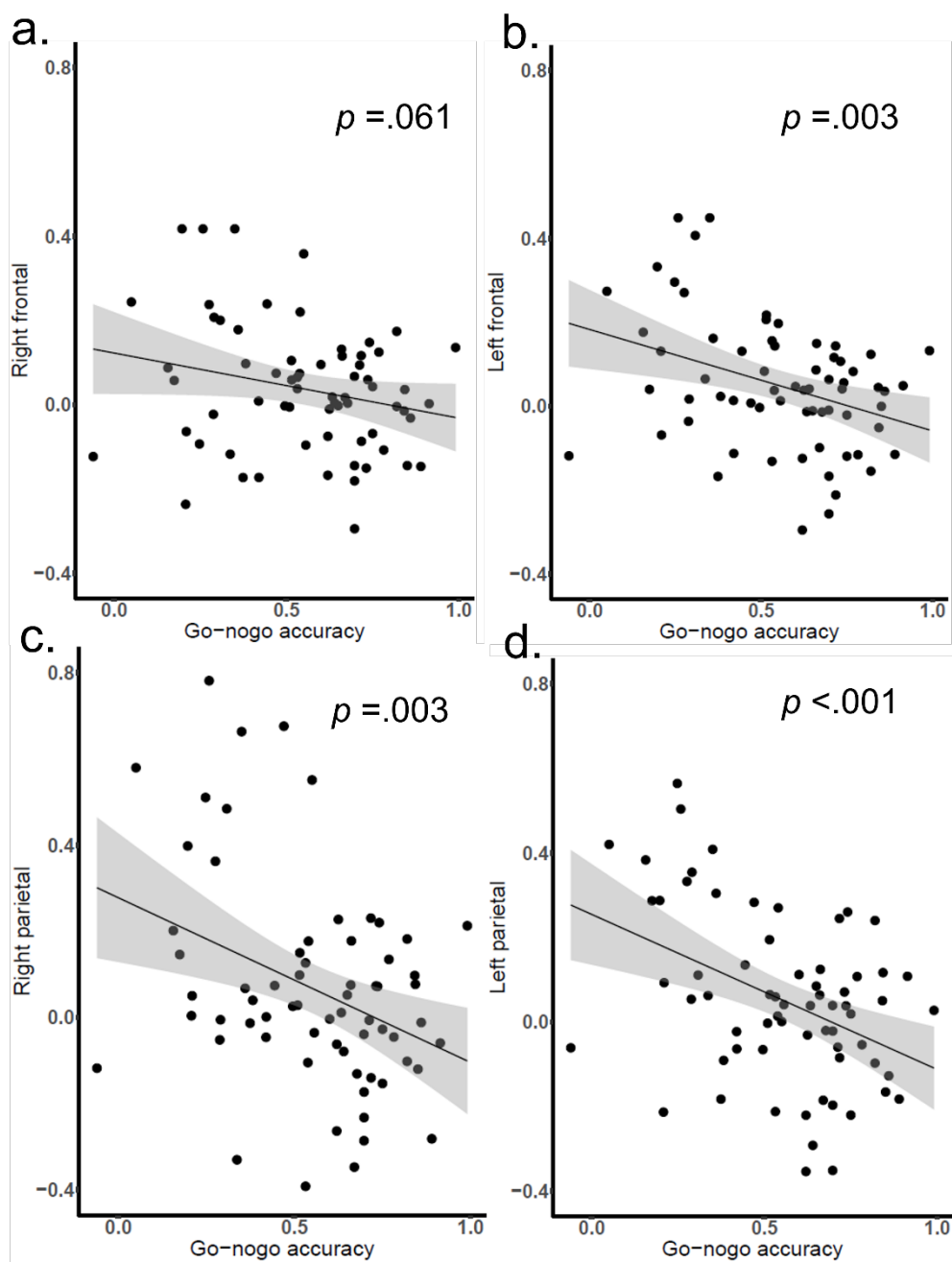
Figure 17. Correlation plots showing negative association between $Go_{correct}$-$NoGo_{incorrect}$ accuracy and activation in the **(a)** right frontal **(b)** left frontal **(c)** right parietal and **(d)** left parietal.

4.5   Discussion

The current study examined performance differences in the neural circuits underlying IC in a group of 4.5-year-old children. Specifically, fNIRS data were collected on children while they completed a go-no/go task in their homes. The goal of the current investigation was two-fold: first, to investigate the neural networks underlying performance differences in pre-schoolers IC, and second, to determine whether these differences were related to parent-reported measures of the child's behaviour and their environment.

As expected, behavioural results indicated that accuracy was significantly worse for no-go trials than for go trials. These findings are in agreement with previous work using the go-no/go task in young children (Bezdjian et al., 2009; Brod et al., 2017; Miao et al., 2017; Smith et al., 2004). Further, as predicted, LPs showed a greater difference in activation between go and no-go trials than HPs in channels overlying the right frontal cortex, the left frontal cortex, the right parietal cortex, and the left parietal cortex. One interpretation for this finding is that LPs may have recruited these regions to a larger extent than HPs due to the increased strain on their inhibitory processes. While this is the first study to specifically examine performance differences in a sample of 4.5-year-old children, and thus the first to report this result, support for this finding stems from previous EEG literature that has examined performance differences in adults. For instance, Jodo & Kayama (1992) used a modified go/no-go paradigm where adults were given either 300 ms or 500 ms to respond and found the no-go N2 amplitude was significantly larger for adults who were required to respond in 300 ms. While the authors concluded that the increased amplitude of the N2 was due to an increase in inhibitory demands, they did not compare behavioural performance between the two groups and thus it is unclear whether the time constraint also led to a decrease in performance. Band et al. (2003) improved upon this limitation by dividing participants into a speed condition (where subjects had to prioritise speed) and a balance condition (where subjects had to prioritise accuracy and speed). They found that prioritising speed negatively affected behavioural responses and led to an increase of the N2 component in response to no-go trials. Lastly,

Benikos et al. (2013) extended these findings using a modified version of the go/no-go task that included three levels of difficulty: low (where stimuli were timed at 1000 ms), medium (where stimuli were timed at 500 ms) and high (where stimuli were timed at 300 ms). They showed that behavioural performance decreased with each increase in task difficulty, while the N2 component increased in amplitude and occurred earlier.

An important difference between the present study and the previous research described above is the current study did not manipulate task difficulty to investigate performance differences, but rather, categorised children into low and high performing groups using a median split. This method was however employed by Smith et al. (2006), who administered an auditory cued go/no-go task and split their subjects according to median reaction time. Although Smith et al. (2006) found no increases in the N2 amplitude in response to no-go trials for the group with faster reaction times, they did find a larger no-go P3 over fronto-central regions in the fast responders. The authors suggested the lack of a no-go N2 effect may have been due to the type of task employed, as the N2 effect has been shown to be weaker in response to auditory than to visual stimuli (Falkenstein et al., 1995, 1999).

A related interpretation stems from research that has investigated inhibition across the lifespan and reported an age-related decrease in activation across the frontal and parietal regions subserving inhibition (Durston et al., 2002; Mehnert et al., 2013). For instance, Braet et al. (2009) administered a go/no-go task and found that compared to adults, adolescents showed increased recruitment of a widely distributed network, including left (inferior, superior and middle) and right (middle and inferior) frontal gyri, left and right insulae, bilateral anterior and posterior cingulate, as well as both left and right inferior parietal cortex and left and right precunei and cunei. The authors argued that the improved behavioural performance and reduced brain activation in adults suggests that the neural network underlying response inhibition becomes more sparsely represented in the brain across development. Further, Tamm et al. (2002) examined performance on a go/no-go task in 8- to 20-year-olds and found both positive and negative age-related effects on inhibition.

Specifically, they reported children showed greater activation in the left superior and middle frontal gyri, while adults showed increased focal activation in the left inferior frontal gyrus. The authors concluded children may show more diffuse prefrontal activation as they lack the cognitive resources required for efficient response inhibition. Consequently, children may employ less efficient strategies that require greater recruitment of more widespread brain regions. Thus, it may be that LPs in the current study employed less efficient strategies that led to a larger recruitment of frontal and parietal areas than HPs.

Interesting parallels can be drawn between the results of the current study and those reported in Chapter 2. Specifically, Chapter 2 investigated performance on a VWM task and found LPs showed a greater difference in activation between the highest and the lowest load than HPs in the left frontal cortex, right parietal cortex and left parietal cortex. In order words, both in the current study and in Chapter 2, poorer performance was characterized by greater recruitment of frontal and parietal regions, supporting the notion that similar neural components are involved in WM and IC (McNab et al., 2008). Further, the go/no-go task includes a WM component as children are required to hold a rule in mind (i.e do not press for cat), in addition to suppressing a prepotent response (i.e press for dog). There has been evidence to suggest that performance is negatively affected when the frontal cortex is required to perform multiple EF's (Luciana & Nelson, 1998). Thus, it might be that LPs here were less efficient at integrating these EF's (specifically, WM and IC) resulting in poorer performance and greater recruitment of these brain regions. Some support for this interpretation can be seen when comparing LPs in the current study with those in Chapter 2. Specifically, 60% of children who were categorised as LPs during the go/no-go task were also considered LPs during the VWM task, suggesting poor performance on the go/no-go task may be due (in part) to WM constraints.

Correlational analyses were additionally run to determine whether factors from the parental questionnaires were related to the performance differences found in brain and behaviour. However, no significant relationships emerged. This is somewhat surprising given the wealth of previous research that has

found associations between response inhibition and childhood temperaments (Aksan & Kochanska, 2004; Wolfe & Bell, 2004) as well as aspects of the home environment (Hassan et al., 2019; Sarsour et al., 2011; Xing et al., 2019). Although previous research has specifically linked deficits in children's performance on the go/no-go task to environmental factors such as SES (St. John, Finch, et al., 2019; St. John, Kibbe, et al., 2019), there are several possible reasons for why the current study did not replicate this finding. First, parental educational attainment was comparable between the HP and LP groups, with 100% of HP children and 88% of LP children having at least one parent who attained a BSc degree or higher. Second, the net annual household income was higher than the national average for both the HP group and the LP group, and the groups did not differ significantly. Thus, it is likely that there was not enough variation in the sample to identify relationships between performance and SES. The lack of variation in SES may be due to the recruitment strategy employed here. Specifically, study information was sent to gateway organisations such as schools, nurseries, and leisure centres. Interested parents then got in touch with the research team who went over the criteria for inclusion. If eligible parents / children met the criteria, a testing session was scheduled. As parents had to volunteer for the research, this strategy may have led to a volunteer bias. Rosenthal (1965) published an extensive review of the literature and found that in general, volunteers for research tended to be female, well educated, and from a higher social class, to name a few. Another limitation of the current study is related to the number of questionnaires included. Specifically, five parent questionnaires were administered which resulted in 31 subscores, and subsequently, 31 tests that had to be corrected for. As a result, none of the correlations survived the correction. Future work could improve upon this by crafting a more focused research question, limiting the number of questionnaires required. Finally, it is important to acknowledge that although home-testing allows children to compete the task in a more relaxed environment than is afforded by traditional laboratory experiments, the home may also contain more distractions which might have influenced performance on the task. Future studies should assess if

the brain-behaviour responses observed in children during testing in their home environment can be similarly observed under controlled lab conditions.

To conclude, an interesting pattern of results emerged in this investigation. Results revealed that LPs showed a greater difference in activation between go and no-go trials than HPs, suggesting that lower performance on a go/no-go task is related to larger recruitment of the frontal and parietal regions. However, this increase in activation was not related to aspects of the child's temperament or home environment. These key findings are an important first step toward understanding individual differences in the development of the neural networks underlying pre-schooler's response inhibition.

CHAPTER 5 DISENTANGLING AGE AND SCHOOLING EFFECTS ON INHIBITORY CONTROL DEVELOPMENT: AN fNIRS INVESTIGATION

Courtney A. McKay, Sobanawartiny Wijeakumar, Eva Rafetseder, Yee Lee Shing

5.1 Abstract

Children show marked improvements in EF between four and seven years of age. In many societies, this time period coincides with the start of formal school education, in which children are required to follow rules in a structured environment, drawing heavily on EF processes such as IC. This study aimed to investigate the longitudinal development of two aspects of IC, namely response inhibition and response monitoring and their neural correlates. Specifically, we examined how their longitudinal development may differ by schooling experience, and their potential significance in predicting academic outcomes. Longitudinal data was collected in two groups of children at their homes. At T1, all children were roughly 4.5 years of age and neither group had attended formal schooling. One year later at T2, one group (P1, $N = 40$) had completed one full year of schooling while the other group (KG, $N = 40$) had stayed in kindergarten. Behavioural and brain activation data (measured with fNIRS) in response to a go/no-go task and measures of academic achievement were collected. We found that P1 children, compared to KG children, showed a greater change over time in activation related to response monitoring in the bilateral frontal cortex. The change in left frontal activation difference showed a positive trend with mathematical ability, suggesting a certain functional relevance of response monitoring for academic performance. Overall, the school environment is important in shaping the development of the neural network underlying the monitoring of one own's performance.

5.2 Introduction

The developmental period of transitioning from kindergarten to formal schooling is characterized by remarkable improvements in cognitive functions. As children prepare for and settle into school and classroom environments, they are increasingly expected to orchestrate and exert control over their own thoughts and behaviors, in accordance to goals and context – a set of skills collectively known as EF (Diamond, 2013). In this study, we investigated the longitudinal development of a key component of EF, namely IC and its neural correlates, how these differ by schooling experience, and their potential significance in predicting academic outcomes.

There is accumulating evidence to suggest IC, the capacity to interrupt a prepotent response and enact an alternative less salient response associated with goal attainment, may play a key role in determining school readiness (Müller et al., 2008) as well as predicting future academic achievement (Blair & Razza, 2007; Duckworth et al., 2019; Gawrilow et al., 2014; McClelland et al., 2014; Smith-Donald et al., 2007; Son et al., 2019). For instance, Bierman and colleauges (2008) found that, in a sample of typically developing preschool children, tasks of WM and IC predicted emerging literacy skills. This finding is an agreement with Blair and Razza (2007), who examined the role of self-regulation in relation to emerging academic abilities in 3- to 5-year-old children. While several aspects of self-regulation predicted certain academic outcomes, IC made independent contributions to all three measures of academic ability (mathematical knowledge, letter knowledge, and phonemic awareness). The authors suggested that the ability to inhibit distracting or irrelevant information while reading or when faced with a numerical problem may be a contributing factor to success, over and above specific knowledge of problem solutions. For example, IC may allow children to consider multiple dimensions of a problem, rather than focusing on the most salient or recent aspects.

While IC prior to starting school may play an important role in predicting future academic success, the school environment itself may play an equally important role in shaping these skills. In school, children are required to follow classroom rules, sit still, and pay attention for a large portion of the lessons

while suppressing any distractions that may interfere with their learning (Bierman et al., 2008). These demands draw heavily on inhibitory processes. Therefore, it is conceivable that the environment of formal schooling may advance the development of IC, in comparison to kindergartens that tend to be more play-oriented (Morrison et al., 1997).

School cut-off design

To estimate the causal effects of schooling on cognitive development is not trivial, as schooling and development are confounded in time. The cut-off design (for a review, see Morrison et al. 2019) is an effective longitudinal method for examining unique schooling effects by taking advantage of arbitrary school cut-off dates. This method compares children who are similar in age, but due to fixed entry dates, are enroled into different school years. Previous studies with a cut-off design found causal, beneficial effects of schooling on aspects of literacy (Morrison et al., 1995; Varnhagen et al., 1994) and numeracy (Bisanz et al., 1995; Christian et al., 2000). Recent years have seen a growth in research examining schooling-related effects on more basic cognitive processes, such as EF, given the associations shown between its subcomponents with academic achievement (Morrison et al. 2019). However, the findings here are mixed. For instance, Burrage et al. (2008) assessed inhibition in two groups of 5-year-old children born within 4 months of each other during the fall and spring semesters of the school year. The researchers found no significant difference in performance between children who had attended school and those who had stayed in kindergarten. On the other hand, Kim and colleauges (2021) used a school cut-off design to examine performance on an IC task in 4- to 7-year-old children. There was a significant difference between first grade children and kindergarten children, with kindergarteners showing greater improvements across the year. However, this result should be interpreted with caution for several reasons. First, based on the data presented, it appears the first-grade children may have been significantly older than the kindergartners at baseline, which was not controlled for in the

analyses. Second, initial differences existed between the two groups at the start of the year, with the first graders outperforming the kindergarteners at baseline. Hence, it is unclear whether the kindergarteners improved more from the experience of kindergarten or were just "catching up" in performance with age.

Despite the growing interest in how schooling may influence various aspects of basic cognition, there have been very few neurodevelopmental investigations. The only longitudinal inquiry into schooling- effects on neural correlates of IC was conducted by Brod and colleauges (2017). Using a cut-off design, fMRI data was collected on 5- and 6-year-old children while they completed a go/no-go task. This study sought to uncover schooling-related effects in *response inhibition*, and thus focused on activation for successfully inhibited (no-go) and successfully executed (go) trials. While no group differences in activation were found during correct no-go trials, a larger increase in activation in the right superior PPC, an area associated with sustained attention, was found for correct go trials, only in children who attended school. The authors concluded the increased engagement of the PPC may reflect a direct effect of the schooling experience, where children are required to pay attention for extended periods of time in classrooms.

Response monitoring

Although trials with correct responses have traditionally been the focus of analyses in a go/no-go task, a separate literature have highlighted a unique pattern of activation in response to errors. First recognized by ERP researchers (Falkenstein et al., 1991; Gehring et al., 1993), the negative and positive components that arise following an incorrect response to a no-go trial are referred to as the error-related negativity (ERN) and error-related positivity (Pe). These components presumably reflect a network of structures, including the anterior cingulate cortex (ACC) and lateral prefrontal cortex (LPFC), and are thought to reflect error detection and/ or conflict resolution processes associated with *response monitoring* (Grammer et al., 2014; Kim et al., 2016).

Interestingly, response monitoring is one of the components of cognitive control that has been linked to academic success (Denervaud, Knebel, et al., 2020; Kim et al., 2016), and its deficits are associated with developmental disorders including ADHD (Groom et al., 2013). To be successful in school, children must monitor their own progress, detect errors when they occur, and subsequently adapt their own behaviour. In comparison to kindergarten, teachers in school classrooms also provide more directive feedback on the accuracy of children's schoolwork, possibly shaping their sensitivity to errors (Denervaud, Knebel, et al., 2020). Relating response monitoring and schooling, Grammer et al. (2014) administered a go/no-go task to a sample of 3- to 7-year-old children and found that Pe was sensitive to age-related change during the school transition period, where older children exhibited a larger Pe than younger children. Further, Kim et al. (2016) administered a go/no-go task alongside two measures of academic achievement; math and reading. Using a multiple regression analysis, they found that stronger reading and math skills predicted a larger Pe but did not predict the ERN. Thus, the authors concluded that the Pe, rather than the ERN, may be associated with academic achievement. Most developmental research in response monitoring has been conducted using EEG, with a handful of studies that have used fMRI (Denervaud, Fornari, et al., 2020; Rubia et al., 2007). Specifically, Rubia and colleauges (2007) compared brain activation between adults and children while they completed a modified stop task. During unsuccessful stop trials (contrasted with successful go trials), adults and children showed similar activation in the medial prefrontal cortex, anterior, and posterior cingulate gyrus. However, adults showed increased activation compared to children in the ACC. Thus, converging evidence from fMRI and EEG investigations has identified neural signatures of response monitoring after committing error, and highlights the involvement of a network of frontal regions.

Present study

Based on the review above, several questions remain that the current study aimed to address. First, although Brod and colleauges (2017) reported that one year of formal schooling results in increased engagement of the PPC, it is unknown whether this increase predicts academic achievement. Previous studies that have investigated the link between response inhibition and academic achievement have been strictly correlational. Thus, any causal links between the two remain to be demonstrated. Second, it is unknown whether entering formal education causally impacts the frontal networks underlying response monitoring. None of the studies that examined response monitoring and schooling utilized a cut-off design. To fill in these knowledge gaps, we conducted a study in Scotland with a modified cut-off design. Rather than comparing children born several months before vs. after a cut-off date, all children in the current study were born in January and February of one year. This was possible because in Scotland, school commencement dates fall in August, with the school-starting cohort consisting of children born between the beginning of March in one year (aged 5.5) and the end of February (aged 4.5) of the following year. However, parents of children born in January and February can choose to enrol their child into school or defer their entry until the following year, and these requests are automatically approved. Thus, the current study compared two groups of children across time: one group enroled into school as soon as they were eligible and completed one year of primary school (P1), and the other group deferred their school entry and stayed in kindergarten (KG). At timepoint 1 (T1) children in both groups were 4.5-years-old and in kindergarten. At timepoint 2 (T2), children in both groups were 5.5-years-old, but P1 children had completed one full year of schooling while KG children had completed another year of kindergarten. Thus, this quasi-experimental design allows for the comparison of two groups of children who are similar in age but differ in their experience in a school context. This is important, given that the kindergarten and schooling environments differ in several ways. Specifically, Sharp (2002) conducted a review of UK and European policy on school starting ages and highlighted four important

differences between the schooling and kindergarten environments. First, children in school spend less time on tasks of their own choosing as schoolteachers take on a more instructional and didactic role. Second, children spend less time outside engaging in physical activities and discovering their environment and instead, spend more time in class sitting still. This is reflected in research conducted by Quick et al. (2002), who found almost half of the British school headteachers interviewed felt their outdoor learning facilities were inadequate. Third, the school curriculum places a larger emphasis on subject-related academic material as opposed to learning through play and finally, the adult to child ratio is usually higher in pre-school settings.

Our first question sought to determine whether entering formal schooling leads to increased engagement of the neural networks underlying response inhibition and response monitoring. To answer this question, we employed a portable fNIRS system, which allowed us to collect data on children in their homes (described in more detail in Chapter 2). This system has several advantages over other imaging modalities as it is non-invasive, cost-effective, portable, and fairly easy to use with young children. Our second question inquired whether schooling-specific improvements in response inhibition and/ or monitoring, if any, would be associated with improvements in academic achievement[2]. In line with findings by Brod et al. (2017), we predicted both groups would show improvements in response inhibition, with P1 children showing a larger increase in parietal activation associated with sustained attention as a result of schooling. Further, based on research suggesting a link between response inhibition and future academic success (Blair & Razza, 2007; Gawrilow et al., 2014; McClelland et al., 2014; Smith-Donald et al., 2007; Son et al., 2019), we predicted the schooling-specific increase in parietal

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[2] This project was pre-registered on As.Predicted.org (#34866). We initially planned to also examine the relationship between performance/neural activation of the go/no-go task with another behavioural EF task that taps into cognitive flexibility (hearts-and-flowers task). However, due to an error in task programming, the data from the hearts-and-flowers task could not be interpreted. Therefore, we focused on children's performance and brain response on the go/no-go task, and relate these to measures of academic achievement.

activation in the P1 children would be associated with larger improvements in academic achievement. Next, we predicted P1 children would, over time, show stronger response monitoring after committing error (i.e., acting wrongly based on prepotent response), and thus show a stronger change in activation in the frontal cortex in response to error trials. Lastly, based on work by Grammer et al. (2014), we predicted schooling-specific changes in response monitoring in the P1 children would be associated with improvements in academic achievement.

5.3 Method

5.3.1 Participants

Participants were recruited through gateway organizations such as nurseries and leisure centers. Parents of eligible children contacted the research team to schedule a testing session. All children had normal or corrected to normal vision, no history of colour-blindness, no neurological conditions, and were born full term (>37 weeks) with an uncomplicated birth. Parents and children provided informed consent prior to testing. The research was approved by the General University Ethics Panel (GUEP 375A – see Appendix E) at the University of Stirling.

Children were tested in their home on two separate occasions, across two consecutive years. At T1, 95 4.5-year-olds were recruited for the study. Fifteen children were excluded from all analyses; 12 children (5 P1, 7 KG) interfered with the fNIRS set-up (pulled the cap off) before the completion of the task, three provided unusable data (two KG children had thick hair that led to poor signal quality, and data from one P1 child was lost due to experimenter error). Hence, a total of 80 children (39 females, Mage at T1 = 53.5 months, SD = 1.2, range = 5 months) provided potentially usable fNIRS data at T1 (see further analysis-specific criteria below). All 80 children agreed to take part at T2 (39 females, Mage at T2 = 65.5 months, SD = 1.2, range = 5 months). Of these children, 40 (24 females, Mage at T2 = 65.6 months, SD = 1.1, $range$ = 5

months) attended P1 in between the two timepoints, and 40 (15 females, *M*age at T2 = 65.4 months, *SD* = 1, *range* = 4 months) remained in KG.

Given the potential associations between task compliance and inhibitory skills, we compared children who refused to participate versus children who agreed to participate on a broad range of questionnaire variables. These questionnaires assessed factors such as child temperament, quality of the parent-child relationship, and SES status (details provided in Chapter 2). We found a significant group difference in three subscores of the Parenting Stress Index (Abidin et al., 2013). The first subscore measured child hyperactivity (p=.022), with those who did not participate scoring higher on this scale. However, we also found that children who did not participate were scored as less demanding (p=.008), and their parent had a better relationship with their partner (p=.036). It is important to note however that these correlations do not survive a correction for multiple comparisons.

fNIRS analysis exclusion (see Figure 18):

Response Inhibition. Two children (1 P1, 1 KG) were excluded from the response inhibition fNIRS analyses for contributing fewer than six usable correct no-go trials across both timepoints and five children were excluded for providing incomplete data (two children (2 KG) refused to complete the task and data from three children (2 P1, 1 KG) was corrupted). Hence, a total of 73 children contributed longitudinal data for the response inhibition fNIRS analyses. Of these children, 37 were in P1 group and 36 were in KG group.

Response Monitoring. Fifteen children (8 P1, 7 KG) were excluded from the response monitoring fNIRS analyses for contributing fewer than six usable incorrect no-go trials across both timepoints, and four children were excluded for providing incomplete data (one KG child refused to complete the task and data from three children (2 P1, 1 KG) was corrupted). A total of 61 children contributed to the response monitoring fNIRS analyses. Of these children, 30 were in P1 group and 31 were in KG group.

Behavioural exclusion:

Vocabulary (administered at T1 and T2). Three children were excluded from the vocabulary analyses (two children (1 P1, 1 KG) refused to do the task and data from one KG child was lost due to experimenter error). 77 children contributed to the final vocabulary analyses. Of these children, 39 were in P1 group and 38 were in KG group.

Numeracy (administered at T1 and T2). Six children were excluded from the numeracy analyses (five children (3 P1, 2 KG) refused to complete the task and data from one KG child was lost due to experimenter error). 74 children contributed to the final numeracy analyses. Of these children, 37 were in P1 group and 37 were in KG group.

School achievement packs (administered at T2 only). No children were excluded on either the math or phoneme pack.
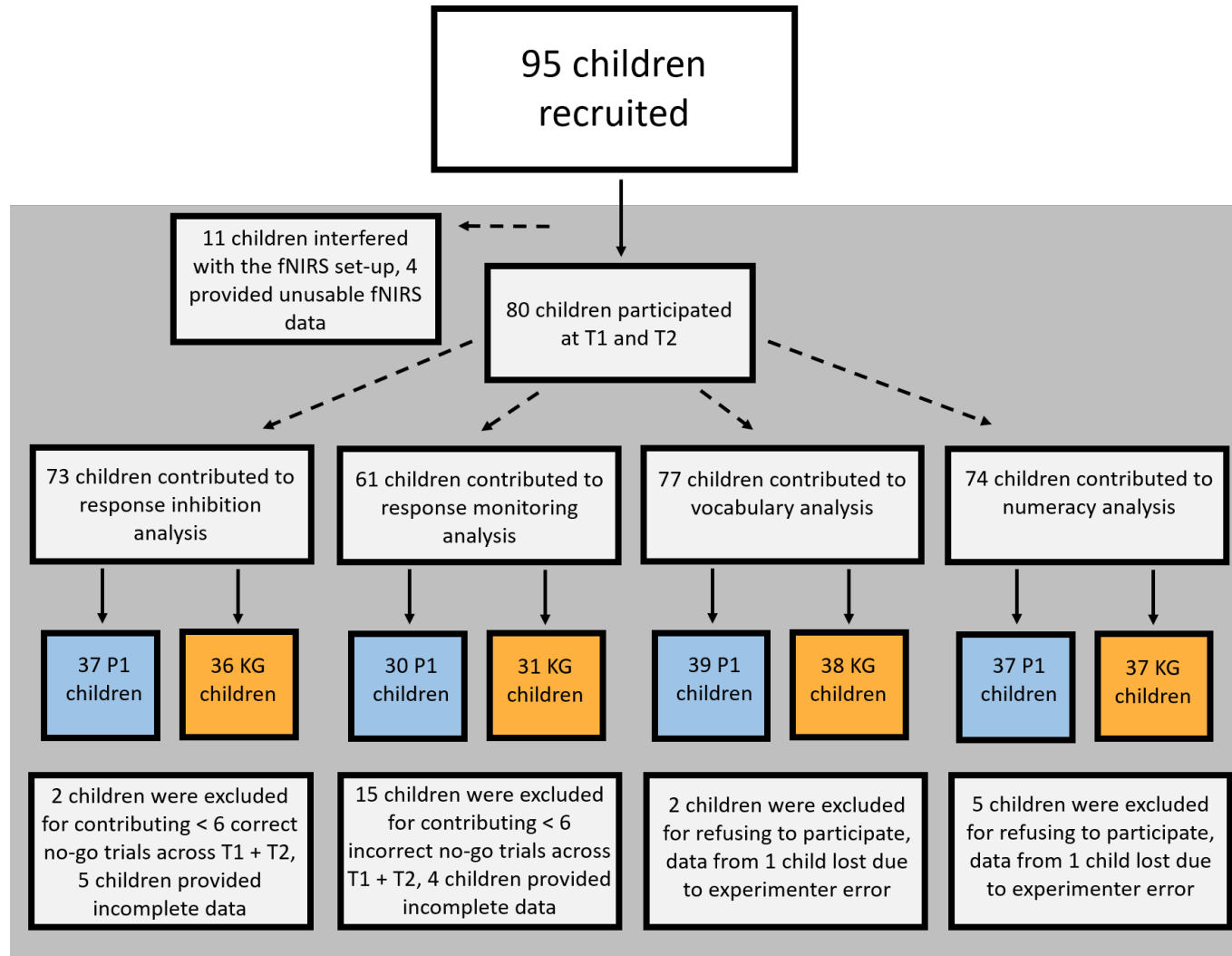
Figure 18. Schematic figure for participant recruitment and data exclusion.

5.3.2 Experimental task

Inhibitory control task

The CDT, adapted from Brod et al. (2017), was used to measure response inhibition and response monitoring in children – see Figure 13. The task was run in E-prime V.3 software on a HP laptop with a 14-inch screen. During "go" trials, children saw a picture of a dog and were supposed to press a button (spacebar). During "no-go" trials, children saw a picture of a cat and were supposed to withhold pressing a button. To ensure children understood the rules, the session began with 3 blocks of practice that progressively allowed less time to response. During the practice, children were reminded of the rules if they made a mistake. Performance on the practice runs was not included in final analyses. After children completed all practice blocks, the test session, consisting of two runs began. The first run was comprised of 59 trials: 44 go trials and 15 no-go trials. Run 2 was comprised of 69 trials: 52 go trials and 17 no-go trials. Pictures of cats and dogs were presented for 500ms, followed by a fixation cross as jitter that ranged in duration from 2 to 8 seconds. Responses made during stimuli presentation or during the fixation cross period were recorded. The order of presentation of go and no-go trials was pseudorandom, with the constraint that no-go trials were preceded equally often by 1, 2, 4 or 5 go trials.

5.3.3 Academic performance measures

Vocabulary task (administered at T1 and T2)

The vocabulary subset of the Wechsler Preschool and Primary Scale of Intelligence (Warschausky & Raiford, 2018) was used to assess word knowledge. The task included 3 picture items and 20 verbal items. During the picture items, children were presented with 3 consecutive pictures of objects (car, scissors, banana) and asked to name each object. If a child incorrectly named the first object (car), they were corrected. Feedback was not provided for the other two picture items. For the verbal items, children were required to

provide verbal definitions of words. Corrective feedback was given for the first two verbal items if a child did not receive a perfect score. No feedback was provided for the remaining verbal items. In accordance with the manual, if a child's response was unclear or too vague, the experimenter prompted the child by asking, "What do you mean", or "Tell me more about it", or some other neutral query. The test was discontinued if a child gave three consecutive incorrect responses. The picture and verbal items were summed to provide a total vocabulary score (out of 43) at each timepoint.

Numeracy task (administered at T1 and T2)

The numeracy screener developed by Nosworthy and colleagues (2013) was used to assess basic numeracy skills. Children were required to compare pairs of magnitudes ranging from one to nine and judge which was larger. Magnitudes were represented symbolically (56 digit pairs) and non-symbolically (56 pairs of dot arrays). In both the symbolic and non-symbolic conditions, numerical magnitude was counterbalanced for the side of presentation. Dot stimuli were also controlled for area and density. Easier items were presented first, followed by more difficult items. Children were given one minute to complete each condition. The order of the two conditions were counterbalanced across participants. Children received one point for each correct answer. A final score was calculated at each timepoint by subtracting incorrect responses from correct responses.

School achievement packs (administered at T2 only)

Two measures of achievement were included to assess how much P1 children learned over the course of the first grade in terms of school content. The math pack contained 25 math questions, adapted from the Scottish Curriculum For Excellence teaching resources (*twinkl*, n.d.). The test was discontinued after 3 incorrect responses. The phonemes pack contained 20 questions assessing phonetic awareness, adapted from the Heggerty Phonemic Awareness

Program (Heggerty, 2019). The pack included 10 items requiring the addition of a phoneme, and 10 items requiring the substitution of a phoneme. A final score for each pack was calculated by summing the correct responses.

5.3.4 fNIRS data acquisition

fNIRS data were collected at 7.81 Hz using a NIRSport system 8x8 (8 sources 8 detectors) / release 2.01 with wavelengths of 850 and 760nm. Fiber optic cables carried light from the machine to a NIRS cap. Probe geometry was designed by collating regions of interest (ROI) from previous fNIRS and fMRI literature (Brod et al., 2017; Wijeakumar et al., 2015). Probe geometry consisted of four channels each on the left and right frontal cortices, and three channels each on the left and right parietal cortices (see Figure 2). Note that short-source-detector channels were not used to regress scalp hemodynamics as all the channels were directed toward maximising coverage of the frontal and parietal cortices. Four cap sizes (50cm, 52cm, 54cm, and 56cm) were used to accommodate different head sizes. Source-detector separation was scaled according to cap size (50cm cap: 2.5cm; 52cm cap: 2.6cm; 54cm cap: 2.7cm and 56cm cap: 2.8cm). To synchronise behavioural and fNIRS data, a McDaq data acquisition device (www.mccdaq.com) was used to send information from the task presentation laptop to the fNIRS system.

5.3.5 Procedure

Data was collected in each participant's home. After arrival, the researcher measured the circumference of the child's head and selected an appropriately sized fNIRS cap. Children were given an iPad to watch cartoons during the set-up. Once the cap was fitted to the child's head, measurements were taken from the inion to the nasion and from the two peri-auricular points to make sure that the cap was centered. After the equipment was safely positioned, the instruction and practices for the CDT started, followed by the actual task. During the task, if children indicated that they made an error (e.g., pressing

after a cat picture), the experimenter reassured the child and encouraged them to continue concentrating on the game. To keep children engaged, each test run contained different pictures of cats and dogs. To maintain motivation, children were also rewarded with a sticker after each run.

Once children completed the CDT, they were provided the iPad© to watch cartoons while the researchers removed the cap. After a short break, the testing proceeded with the vocabulary task, followed by the numeracy task. At T2, children were additionally tested on the phonemes pack and math pack. The order of the academic performance tasks were presented was counterbalanced across participants. Children were rewarded with stickers after completing each task, regardless of their performance. All children were remunerated with £10 and a toy upon completion of each time point measurement.

5.3.6 Behavioural analyses

Accuracy was calculated separately for each trial type (go and no-go) and test run (run 1 and run 2) and timepoint (T1 and T2). The following formula was used to calculate accuracy and RT at each timepoint to account for the different number of trials included in each run.

$$\text{Weighted average} = \frac{\big((\text{run 1 score} * \text{run1 number of trials}) + (\text{run 2 score} * \text{run 2 number of trials})\big)}{\text{Total number of trials}}$$

After computing the weighted averages, a corrected measure of accuracy (against response biases) was calculated for each subject, by subtracting no-go incorrect responses from go correct responses ($\text{Go}_{correct} - \text{NoGo}_{incorrect}$), separately at each timepoint.

5.3.7 Outlier correction

All behavioural data were screened for outliers. To correct for longitudinal outliers, we used the Mahalanobis distance method. Further, we screened for outliers that were ±3 SDs from the mean at each timepoint. Three outliers were identified: two P1 children were removed from the phonemes pack analyses and one KG child was removed from the math pack analyses. No other outliers were identified.

5.3.8 fNIRS preprocessing

fNIRS data were pre-processed using the Homer2 package (https://www.nitrc.org/projects/homer2/). Raw data were pruned using the *enPrunechannels* function (SNRthresh=2, SDrange=0.0 – 45). Signals were converted from intensity values to optical density (OD) units using the *Intensity2OD* function. Data was corrected for motion using the *hmrMotionCorrectPCArecurse* function, (tMotion=1, tMask=1, STDEVthresh=50, AMPthresh=0.5, nSV=0.97, maxIter=5, turnon=1). Data was scanned for motion artifacts using *hmrMotionArtifactByChannel* function (tMotion=1, tMask=1, STDEVthresh=50, AMPthresh=0.5). Then, the function *enStimRejection* (tRange=-1 to 3) was used to turn off stimulus triggers that contained motion artifacts. The data were band-pass filtered using *hmrBandpassFilt* to include frequencies between 0.016Hz and 0.5Hz. Using the function *hmrOD2Conc*, the OD units were converted to concentration units. To find trials that were outliers with respect to the average HRF, we used the function *hmrFindHrfOutlier* (tRange=-1 to 3, STDEVthresh=3, minNtrials=3). Lastly, the HRF was estimated using the ordinary least squares method with a modified gamma function with a square wave (*hmrDeconvHRF_DriftSS* function [tRange=-1 to 3, paramsBasis=0.1,0.5,0.5, rhoSD_ssThresh=0, flagSSmethod=0, driftOrder=3, flagMotionCorrect=0]).

5.3.9   fNIRS group analyses

HbO and HbR beta values were extracted for each run (run 1 and run 2) and each condition (go cue correct trials, no-go cue incorrect trials, go cue incorrect trials, no-go cue incorrect trials, response go trials, response no-go trials). A weighted average was then calculated to account for the different number of trials included in each test run to produce one beta estimate per subject, per condition, per chromophore, and per timepoint.

Response inhibition analyses

For the response inhibition analyses, we focused on HbO and HbR betas estimates for go cue correct trials and no-go cue correct trials. These beta values captured activation right after the onset of the stimulus. At T1, the mean number of correct trials included for P1s were 60 ± 4 go trials and 16 ± 1 no-go trials. The mean number of correct trials included for KGs were 66 ± 3 go trials and 18 ± 2 no-go trials. At T2, the mean number of correct trials included for P1s were 69 ± 4 go trials and 19 ± 1 no-go trials. The mean number of correct trials included for KGs were 75 ± 4 go trials and 18 ± 1 no-go trials.

Response monitoring analyses

In the pre-registration, we initially only planned for analysis of response inhibition, focusing on correct responses on no go trials. However, based on consideration from the literature (Grammer et al., 2014) we also investigated activation relating to response monitoring, namely contrasting erroneous responses on no-go trials against correct response on go trials. In both trial types a motor response was conducted, followed by no explicit feedback. Therefore, the post-processing of the erroneous response in the case of no-go trials is assumed to involve the detection of error and conflict, which should lead to more monitoring and careful responding in subsequent trials, and consequently overall better performance on the task. Thus, for the response monitoring analyses, we focused on HbO and HbR betas estimates for response on go trials and response on no-go trials. These beta values captured activation at the onset of the child's button press. At T1, the mean number of trials included for P1s were 61 ± 4 correct go trials and 12 ± 1 incorrect no-go

trials. The mean number of trials included for KGs were 65 ± 4 correct go trials and 10 ± 1 incorrect no-go trials. At T2, the mean number of trials included for P1s were 69 ± 4 correct go trials and 9 ± 1 incorrect no-go trials. The mean number of trials included for KGs were 74 ± 4 correct go trials and 12 ± 1 incorrect no-go trials.

5.3.10 Modelling framework

Univariate LCS models (Kievit et al., 2018; McArdle & Hamagami, 2004) were used to investigate the degree of change of the tasks with longitudinal data. All univariate models were set up as multi-group models, allowing the same model to be fitted for each group (P1 vs. KG) and later on parameter comparisons. Individual growth is captured by T1 (i.e., the intercept of *X1_T1* – Figure 11) and the latent change score factor ($\Delta X1$), modelled as the difference between the initial observation and subsequent observation. Average group change across time is captured by the mean of the latent change score factor ($\mu_{\Delta X1}$), and between-person differences in change are captured by the variance ($\sigma^2_{\Delta X1}$). Lastly, the covariance or regression parameter ($\beta_{XT1\Delta X1}$) determines to what extent the amount of change depends on scores at T1.

With the inclusion of an extra domain, a univariate LCS model can be extended into a bivariate LCS model, allowing for testing of cross-domain coupling (see Figure 11). To determine whether scores at T1 in one domain (*X1*) are associated with scores at T1 in a second domain (*X2*), the intercept covariance (ρ_{X1X2}) is estimated. To examine whether the change in *X1* is associated with the change in *X2*, the change covariance is estimated ($\rho_{\Delta X1\Delta X2}$). Further, the coupling effect *($y2_{X1\Delta X2}$)* determines whether the change in *X1* is a function of the starting point of *X2,* and vice versa *($y1_{X2\Delta X1}$).* For the bivariate LCS model, as motivated by our second research question, only measures that showed schooling-specific effects, from response inhibition/monitoring on the one hand, and academic performance, on the other hand, were included.

5.3.11 Model fit indices

Models were estimated in the lavaan software package in R (version 3.6.2, 2019; Rosseel, 2012). Full information maximum likelihood was used for model estimation and to handle missing data. To test for significance of parameters of interest, equality constraint was made on the parameter and significance of change in model fit (compared to the just-identified free model) was assessed using the chi-square difference test (at $p<$ .05). To account for any age and gender effects, these variables were added as covariates of interest into all models.

5.4   Results

5.4.1   Behavioural results - Univariate LCS modelling

Four separate univariate models were fitted to each group (P1 and KG) with (1) corrected accuracy on CDT ($Go_{correct}$-$NoGo_{incorrect}$) (2) vocabulary scores (3) symbolic numeracy scores (4) non-symbolic numeracy scores. Raw mean performance levels are illustrated in Figure 19. Parameter estimates are shown in Table 6.

   CDT. P1 children showed a significant increase in corrected accuracy between T1 and T2, while KG children did not. However, when the change in corrected accuracy was constrained to be equal across groups, model fit was not significantly worse, Δx^2 = 1.237, Δdf = 1, p = .266. There was also no significant worsening in model fit when the baseline scores at T1 were constrained to be equal across groups Δx^2 = .189, Δdf = 1, p = .664. This suggests that P1 children and KG children started out with similar accuracy and changed comparably across the two timepoints, contrary to our hypothesis.

   Vocabulary. Both P1 children and KG children showed a significant increase in vocabulary scores between T1 and T2. Constraining the change to be equal across groups led to a significant drop in model fit Δx^2 = 5.001, Δdf = 1, p = .025, suggesting P1 children increased significantly more than KG children. No significant differences at T1 were found

$\Delta x^2 = .084$, $\Delta df = 1$, $p = .772$. Therefore, P1 children and KG children started out with similar accuracy, but the improvement in P1 children on vocabulary knowledge was greater than the improvement in KG children.

Numeracy. For the symbolic condition, both P1 children and KG children showed a significant increase in scores between T1 and T2. No significant drop in model fit was found when the change was constrained to be equal across groups $\Delta x^2 = .413$, $\Delta df = 1$, $p = .520$. Further, no significant baseline difference was found when the scores at T1 were constrained to be equal across groups $\Delta x^2 = 3$, $\Delta df = 1$, $p = .083$. For the non-symbolic condition, P1 children significantly improved between the two timepoints while KG children did not. However, when the change was constrained to be equal across groups, no significant drop in model fit was observed $\Delta x^2 = 2.037$, $\Delta df = 1$, $p = .154$. Further, no significant drop in model fit was found after constraining T1 estimates to be equal across groups $\Delta x^2 = .002$, $\Delta df = 1$, $p = .969$. Thus, for both conditions of the task, P1 children and KG children started out with similar scores and they changed comparably between the two timepoints.

School achievement packs. Univariate models could not be fitted to the school achievement packs as they were only administered at T2, after P1 children had completed 1 year of schooling. Thus, simple t-tests were conducted to compare performance between P1 and KG children on these measures. As expected, we found that P1 children (Math: $M = 30.1$, $SD = 6.6$; Phonemes: $M = 6.4$, $SD = 4$) performed significantly better than KG children (Math: $M = 23.9$, $SD = 6.5$; Phonemes: $M = 2.5$, $SD = 2.7$) on both math and phonemes, respectively ($t[77] = 4.233$, $p < .001$; $t[76] = 5.067$, $p < .001$).
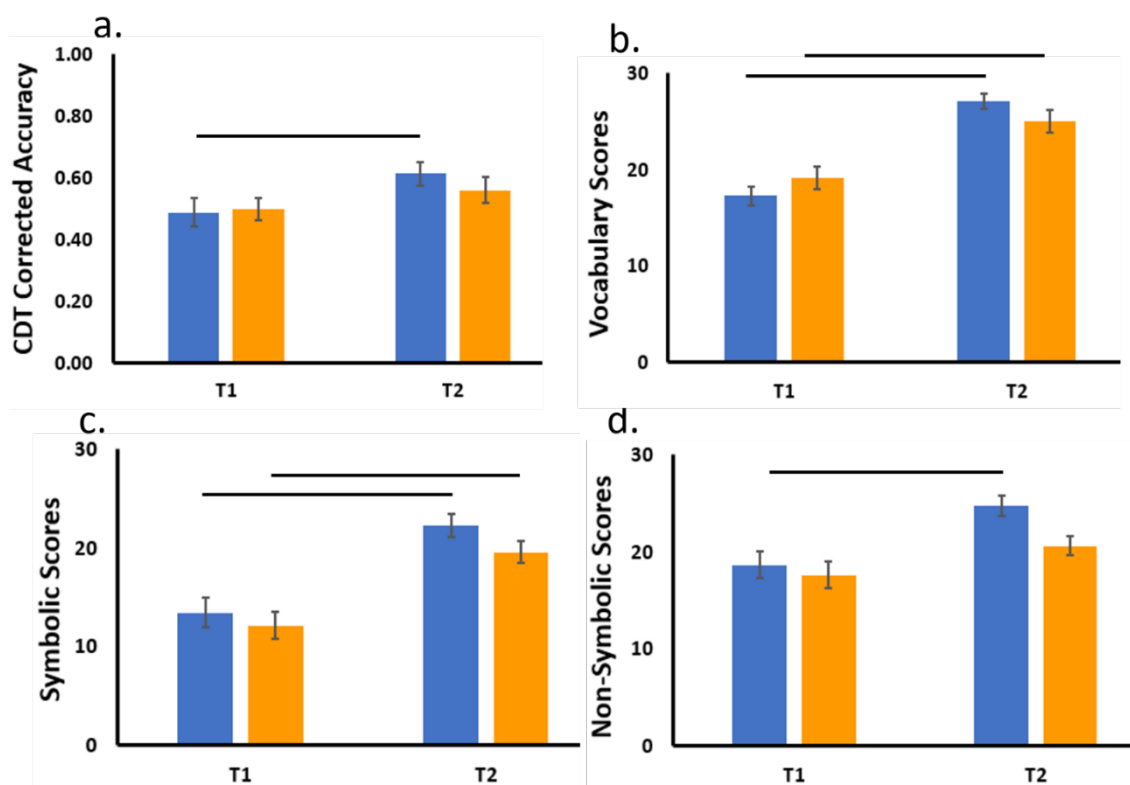
Figure 19. Behavioural estimates for the **(a)** CDT task (corrected accuracy based on $Go_{correct}$-$NoGo_{incorrect)}$ **(b)** vocabulary task **(c)** numeracy task (symbolic) **(d)** numeracy task (non-symbolic). P1 children are shown in blue and KG children are shown in orange. "-" denotes significance at $p < .05$ level (see text for the results of formal model comparison). Error bars show SEM.

Table 6. Parameter estimates for P1 children and KG children from four separate univariate models on the behavioural tasks. Standard errors are in parentheses. [*] Asterisks denote significance at $p < .05$ level. [a] Age = age in days. [b] Gender coded as 1 = girls , -1 = boys.

	$Go_{correct}$-$NoGo_{incorrect}$		Vocabulary		Numeracy (Symbolic)		Numeracy (Non-Symbolic)	
	P1	KG	P1	KG	P1	KG	P1	KG
Mean change $\mu_{\Delta x}$	.13* (.05)	.06 (.05)	9.79* (1.15)	5.72* (1.31)	8.88* (1.53)	7.47* (1.55)	6.18* (1.45)	2.96 (1.66)
Change variance $\sigma^2_{\Delta X}$	.09* (.02)	.08* (.02)	52.59* (13.23)	64.65* (20.55)	91.24* (20.61)	88.9* (17.31)	78.56* (19.06)	105.5* (22.56)
Intercept X_T1	-1.97 (1.58)	-1 (1.57)	-96* (31.63)	-80.03 (44.05)	69.42 (47.81)	-67.68 (63.16)	-10.44 (50.94)	-14.03 (76.52)
Intercept variance σ^2_X	.07* (.01)	.05* (.01)	31.08* (6.41)	46.8* (7.16)	76.26* (24.08)	64.38* (13.33)	65.37* (14.02)	67.13* (14.2)
Intercept-change regression $\beta_{XT1\Delta X}$	-.05* (.01)	-.03* (.01)	-26.96* (8.23)	-34.18* (10.24)	-56.59* (20.81)	-50.93* (11.86)	-50.22* (12.9)	-67.39* (16.3)
Age[a] onto intercept	.15 (.1)	.09 (.1)	6.88* (1.93)	6.07* (2.68)	-3.41 (2.91)	4.88 (3.87)	1.76 (3.1)	1.94 (4.7)
Age-change covariance	-.03 (.016)	-.02 (.02)	-.92* (.44)	.11 (.35)	.387 (.528)	-.89* (.44)	-.46 (.54)	.12 (.57)
Gender[b] onto intercept	.07 (.04)	.06 (.03)	.9 (.9)	.57 (1.16)	.67 (1.52)	-.09 (1.55)	.48 (1.46)	.38 (1.81)
Gender-change covariance	.01 (.05)	-.02 (.04)	-.87 (1.07)	-.97 (1.33)	-1.9 (1.48)	2.19 (1.62)	-1.54 (1.52)	.84 (1.68)

5.4.2   fNIRS results

fNIRS data were comprised of HbO and HbR beta values for each of the 14 channels. To reduce data dimension and focus subsequent analyses on effects that had a difference between HbO and HbR, an initial repeated measure ANOVA including chromophore (HbO, HbR) as a factor was run for each channel, using the Benjamini-Hochberg method to correct for multiple comparisons. For the response inhibition analyses, a repeated measures ANOVA with a within-subject factor of trial type (go correct, no-go correct) and chromophore (HbO, HbR) and a between-subjects factor of group (P1, KG) was run for each of the 14 channels. For the response monitoring analyses, a repeated measures ANOVA with a within-subject factor of trial type (go correct, no-go incorrect) and chromophore (HbO, HbR) and a between-subjects factor of group (P1, KG) was run for each of the 14 channels. We focused on significant interactions involving chromophore as a factor, and followed up with post-hoc analyses conducted on the HbO estimates.

Response inhibition analyses. Only channels that showed a significant interaction involving chromophore and that survived the Benjamini-Hochberg correction are reported. The interaction between trial type and chromophore was significant in channels overlying the right middle frontal gyrus (F[1,71] = 12.052, p=.001), the right inferior frontal gyrus (F[1,71] = 8.241, p=.005), the right supramarginal gyrus (F[1,70] = 7.932, p=.006), and the left supramarginal gyrus (F[1,71] = 11.876, p=.001). Following up on the interaction, post-hoc tests revealed that HbO activation for go correct trials was greater than activation for no-go correct trials (see Table 7). The remaining 3-and 4-way interactions between group, trial type, time, and chromophore were either not significant or did not survive the Benjamini-Hochberg correction. Post-hoc analyses for the HbR estimates are shown in Appendix G, Table G1.

Table 7. Response inhibition analysis: channels showing significant interactions between trial type (go correct and no-go correct) and chromophore. Significant post-hoc results are shown for HbO estimates.

Channel No.	Brain areas (MNI coordinates)	Trial x Chromophore (HbO)
Channel 1	Right middle frontal gyrus	Go > No-go ($p = 0.007$)
Channel 2	Right middle frontal gyrus	
Channel 3	Right inferior frontal gyrus	Go > No-go ($p = 0.006$)
Channel 4	Right inferior frontal gyrus	
Channel 5	Left middle frontal gyrus	
Channel 6	Left middle frontal gyrus	
Channel 7	Left inferior frontal gyrus	
Channel 8	Left inferior frontal gyrus	
Channel 9	Right angular gyrus	
Channel 10	Right superior occipital gyrus	
Channel 11	Right supramarginal gyrus	Go > No-go ($p = 0.008$)
Channel 12	Left inferior parietal lobule	
Channel 13	Left angular gyrus	
Channel 14	Left supramarginal gyrus	Go > No-go ($p = 0.004$)

Response monitoring analyses. Only channels that showed a significant interaction with chromophore and that survived the Benjamini-Hochberg correction are reported. The interaction between trial type and chromophore was significant in channels overlying the right middle frontal gyrus ($F[1,57] = 21.134$, $p<.001$; $F[1,57] = 15.341$, $p<.001$), the right inferior frontal gyrus ($F[1,57] = 19.023$, $p<.001$), the left middle frontal gyrus ($F[1,57] = 40.548$, $p<.001$), the left inferior frontal gyrus ($F[1,57] = 18.279$, $p<.001$; $F[1,57] = 10.769$, $p=.002$), and the right supramarginal gyrus ($F[1,56] = 6.773$, $p=.012$). Following up on the interaction, post-hoc tests revealed that HbO activation for (erroneous) response at no-go trials was more negative than (correct) response at go trials (see Table 8). Post-hoc analyses for the HbR estimates are shown in Appendix G, Table G2.

A significant 4-way interaction between group, time, trial, and chromophore was observed in channels overlying the right middle frontal gyrus ($F[1,57] = 10.198$, $p=.002$; $F[1,57] = 5.671$, $p=.021$), the right inferior frontal

gyrus (F[1,57] = 7.402, p=.009), the left middle frontal gyrus (F[1,57] = 9.912, p=.003), the left inferior frontal gyrus (F[1,57] = 5.897, p=.018), and the right superior occipital gyrus (F[1,56] = 5.976, p=.018). All post-hoc tests are shown in Table 8. Importantly, in the bilateral middle frontal gyrus and bilateral inferior frontal gyrus, P1 children showed greater negative activation for response at incorrect no-go trials than for correct go trials at both T1 and at T2. This was not the case for KG children, who only showed a difference in activation between these trials at T1. Therefore, the ANOVA revealed that the difference in activation between correct go trials and incorrect no-go trials across time differentiated P1 children from KG children. To relate these neural differences in response monitoring to behavior using the bivariate LCS models, an average difference in activation (go correct activation – no-go incorrect activation) was computed across channels of nearby regions that showed the significant 4-way interaction with similar patterns. Specifically, this led to two clusters covering the right frontal cortex (averaging channels 1, 2, and 3; see Figure 20a) and the left frontal cortex (averaging channels 5 and 7; see Figure 20b).

Table 8. Response monitoring analysis: channels showing significant 2-way interaction between trial type (go correct vs. no-go incorrect) and chromophore, and 4-way interaction between group, trial type, time, and chromophore. Significant post-hoc results are shown for HbO estimates.

| Channel No.	Brain areas (MNI coordinates)	Trial x Chromophore (HbO)	Group x Trial x Time x Chromophore (HbO)
Channel 1	Right middle frontal gyrus	Go > No-go ($p < 0.001$)	P1 T1: Go > No-go ($p = 0.048$) P1 T2: Go > No-go ($p = 0.001$) KG T1: Go > No-go ($p = 0.036$)
Channel 2	Right middle frontal gyrus	Go > No-go ($p < 0.001$)	P1 T1: Go > No-go ($p = 0.013$) P1 T2: Go > No-go ($p < 0.001$)
Channel 3	Right inferior frontal gyrus	Go > No-go ($p < 0.001$)	P1 T1: Go > No-go ($p = 0.004$) P1 T2: Go > No-go ($p < 0.001$) KG T1: Go > No-go ($p = 0.005$)
Channel 4	Right inferior frontal gyrus		
Channel 5	Left middle frontal gyrus	Go > No-go ($p < 0.001$)	P1 T1: Go > No-go ($p = 0.001$) P1 T2: Go > No-go ($p = 0.002$)
Channel 6	Left middle frontal gyrus		
Channel 7	Left inferior frontal gyrus	Go > No-go ($p < 0.001$)	P1 T1: Go > No-go ($p = 0.012$) P1 T2: Go > No-go ($p = 0.001$) KG T1: Go > No-go ($p < 0.001$)
Channel 8	Left inferior frontal gyrus	Go > No-go ($p = 0.025$)	
Channel 9	Right angular gyrus		
Channel 10	Right superior occipital gyrus		P1 T2: Go > No-go ($p = 0.05$)
Channel 11	Right supramarginal gyrus	Go > No-go ($p = 0.042$)	
Channel 12	Left inferior parietal lobule		
Channel 13	Left angular gyrus		
Channel 14	Left supramarginal gyrus		
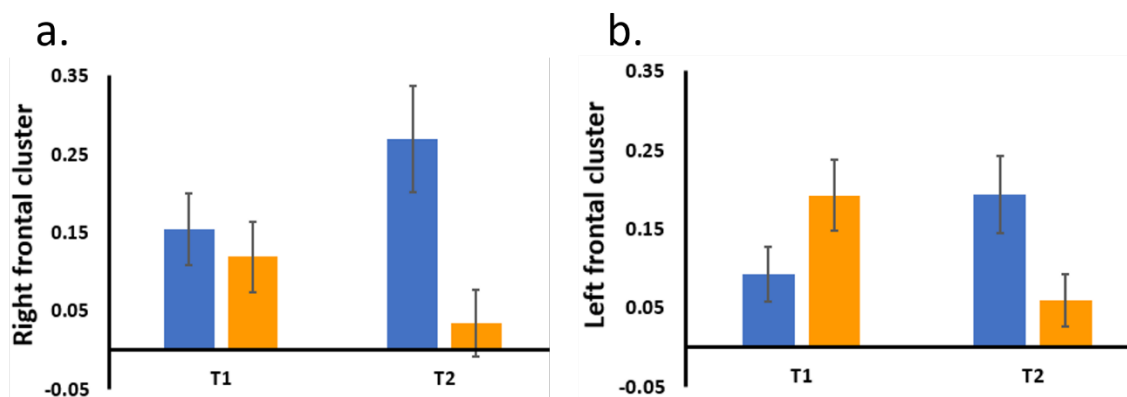
Figure 20. The difference in activation between go correct and no-go incorrect trials (response monitoring contrast) in the **(a)** right frontal cluster **(b)** left frontal cluster. P1 children are shown in blue and KG children are shown in orange. Error bars show SEM.

5.4.3 Bivariate LCS modelling

As the first step, we tested the longitudinal coupling between the activation difference in the two frontal clusters and corrected accuracy on the CDT task for both groups. This is mainly to verify the functional relevance of the two frontal clusters of response monitoring activation for overall task performance.

Right frontal cluster and CDT corrected accuracy. Parameter estimates are shown in Table 9. For KG Children, corrected accuracy at T1 was positively correlated with the difference in activation in the right frontal cluster at T1. Namely, children who showed more difference in activation related to response monitoring had better performance. Constraining the baseline correlation at T1 to be 0 in KG children led to a significant drop in model fit, $\Delta x^2 = 10.707$, $\Delta df = 1$, $p = .001$. No other cross-domain parameters were significant.

For P1 children, corrected accuracy at T1 negatively predicted the change in the difference in activation in the right frontal cluster from T1 to T2. Thus, children with better performance at T1 showed less change in activation over time. However, constraining the coupling pathway to be 0 did not lead to a

significant drop in model fit Δx^2 = 3.776, Δdf = 1, p = .052. No other cross-domain parameters were significant.

Left frontal cluster and CDT corrected accuracy. For KG children, better corrected accuracy at T1 was correlated with higher difference in activation in the left frontal at T1. Constraining the baseline correlation at T1 to be 0 in KG children led to a significant drop in model fit, Δx^2 = 5.028, Δdf = 1, p = .025. Furthermore, higher corrected accuracy at T1 predicted more change in the difference in activation in the left frontal. To follow up on this, the coupling pathway was constrained to be 0 in KG children, which led to a significant drop in model fit Δx^2 = 4.492, Δdf = 1, p = .034.

For P1 children, similar to KG children, better corrected accuracy at T1 was correlated with higher difference in activation in the left frontal at T1. Constraining the baseline correlation at T1 to be 0 in P1 children lead to a significant drop in model fit, Δx^2 = 5.536, Δdf = 1, p = .019. No other cross-domain pathways were significant.

Taken together, in KG and P1 children, higher response monitoring activation difference in the left frontal cluster (additionally right frontal cluster for KG) was related to better overall performance in the inhibitory task.

Table 9. CDT bivariate couplings between **(a)** right frontal cluster and corrected accuracy (Go$_{correct}$-NoGo$_{incorrect}$)and **(b)** left frontal cluster and corrected accuracy (Go$_{correct}$-NoGo$_{incorrect}$), separately for P1 children and KG children. Standard errors are in parentheses. [*]Asterisks denote significance at *p* <.05 level.

	a. Right frontal cluster		b. Left frontal cluster	
	P1	KG	P1	KG
Intercept covariance ρ_{X1X2}	.65 (1.3)	2.97* (.78)	3.32* (1)	1.83* (.82)
Right frontal onto corrected accuracy change $Y1_{X2\Delta X1}$	0 (0)	-.01 (0)	0 (0)	0 (0)
Corrected accuracy onto right frontal cluster change $Y2_{X1\Delta X2}$	-53.5* (22.37)	3.03 (20.73)	-10.1 (19.92)	31.91* (14.6)
Change-change covariance $\rho_{\Delta X1\Delta X2}$	.98 (1.41)	-.47 (1.11)	1.35 (1.31)	1.16 (.73)

Academic Achievement in P1 children

To address our second research question, we tested to what extent the schooling-specific response monitoring activation changes in the two frontal clusters could predict academic achievement. The longitudinal coupling between the activation difference with performance on the academic tasks was examined. Here, we focused on bivariate relationships of P1 children (since they were the only group that attended school and showed a greater response monitoring activation difference across time).

Right/left frontal cluster and academic achievement. Bivariate longitudinal models were fitted for the response monitoring activation in the right frontal (or left frontal, respectively) and (1) vocabulary scores (2) math pack and (3) phonemes pack. The longitudinal change in activation in the left frontal cluster was positively correlated with math pack scores at T2 (*p*=.04). To follow up on this finding, the coupling pathway was constrained to be 0, which

led to a trend drop in model fit Δx^2 = 3.488, Δdf = 1, p = .062. No other cross-domain parameters were found to be significant in all other models.

5.5 Discussion

The present study sought to examine to what extent one year of formal schooling shapes the development of neural processes underlying response inhibition and response monitoring and establish whether these effects were related to academic achievement. First, we found that P1 children and KG children started out with similar corrected accuracy on the go/no-go task. Although P1 children, but not KG children, showed significant improvement on task accuracy over time, the magnitude of change between the two groups was statistically comparable. While we hypothesized that P1 children would show greater improvement than KG children across the year, our findings are in line with Brod et al. (2017) who also reported no group differences in response inhibition behaviour across the year. However, unlike Brod et al. (2017) and in contrary to our hypothesis, we also did not find any group difference in neural activation related to response inhibition (or parietal activation during go trials as in Brod et al. 2017).

Several methodological differences exist that may account for this inconsistency. First, children in the current study were between one to two years younger than the children in the Brod et al. (2017) study, due to national differences in school entry age. The first year of schooling may be set up to be less demanding and formally structured in countries where children start school at a younger age. Thus, the increase in parietal activation resulting from a schooling environment may only appear if there is a sufficiently large change in terms of demand and expectations transitioning from kindergartens to classrooms. Second, the current study and that of Brod et al. (2017) employed different modalities to record brain activation. The fNIRS channel-based analyses employed here may not have been as sensitive as the fMRI analyses conducted by Brod et al. (2017) to detect changes in activation in small clusters of voxels (as reported in that study). A potential way to improve upon this would

be to conduct more targeted analyses. For instance, novel image reconstruction uses a head model to generate functional images of the fNIRS data, transforming surface level channel-based data into a volumetric representation within the brain (Forbes et al., 2021). This would allow for greater comparability with fMRI investigations.

Another limitation of our research may be related to the longitudinal nature of the study. Longitudinal research with fNIRS might carry the risk that the recorded areas do not remain consistent over time, particularly in development when children's brains are actively developing and growing. However, recent work by Collins-Jones et al. (2021) used image reconstruction to investigate the effects of variation in array position and head size in channel-space analysis of longitudinal fNIRS infant data. They found that the inferences drawn from group level channel-based analysis are unlikely to be significantly affected by variability in array position and shifting head sizes, though this effect is more pronounced at the individual level. Further, the present study took several measures to reduce the likelihood that shifting head sizes would interfere with recordings. Care was taken to ensure the appropriately sized cap was chosen for each child based on their head circumference. Furthermore, the experimenters took measurements as precise as possible to ensure the center of the cap was aligned with the center of the child's head.

Finally, Brod et al. (2017) employed a traditional school cut-off design, where children whose birthdates fell shortly before and shortly after an arbitrary cut-off date were compared, resulting in random group assignment. On the other hand, the current study took advantage of school commencement regulations in Scotland, where parents of children born in January and February each year can chose to enrol or defer their child's entry to school. Thus, it is conceivable that parents make this decision based on certain child characteristics, leading to fundamental differences between children who are enroled versus those who are deferred. While this is a consideration worth discussing, the evidence suggests this was not the case. First, P1 and KG children showed no differences in performance at the first timepoint on any of the cognitive and academic measures included here. Secondly, the current

study is part of a larger project that administered a battery of parental questionnaires measuring child temperament, quality of the parent-child relationship, and a range of environmental factors including SES, level of disorganisation in the home, and number of daily hassles experienced by parents. Critically, no differences between P1 and KG children emerged in any of these parent-reported measures, suggesting parents might not accurately perceive whether their child is ready for school. Taken together, the absence of group differences at the first timepoint suggests parental beliefs concerning school readiness are not reflected in quantitative measures of cognitive function, academic performance, and child temperament included here. Nevertheless, it is still possible that the P1 and KG children were different in ways not measured here. For instance, although the questionnaires included in the current study measured parenting behaviours, they did not provide an in-depth assessment of parental personality traits. Future research should collect more detailed information on parental characteristics to determine whether this might influence the decision to enrol or defer, and consequently, lead to differences between the two groups of children.

Second, for activation related to response monitoring, we found that P1 children, but not KG children, showed a greater difference after one year of schooling. As the response monitoring contrast was not part of the study pre-registration, it was important for us to first establish the functional relevance of the two frontal clusters (left and right middle/inferior frontal gyrus) that emerged from this contrast. Therefore, we tested the coupling between the difference in activation with performance on the CDT task, and we found that a greater response monitoring activation difference in the left frontal cluster was related to better performance in the IC task in both groups. For KG children, a similar relationship was also found for the right frontal cluster. This is in line with previous research reporting that a greater difference in activation between correct go and incorrect no-go trials reflects more efficient response monitoring (Grammer et al., 2014; Torpey et al., 2012), which may support better task performance. Previous adult fMRI studies have implicated a broader network of frontal regions subserving response monitoring. For example, Chevrier et al.

(2007) administered a stop-signal task and found error-related activity in frontal regions including the right middle frontal gyrus and dorsal ACC. Furthermore, Edwards et al. (2012) administered a go/no-go task and combined ERP time courses and fMRI spatial maps allowing for the identification of brain regions that are associated with portions of the time course in the ERP data. They identified two components associated with significant activation in the bilateral middle frontal gyrus and caudal ACC, demonstrating that both regions are engaged during error processing. The authors argued the simultaneous involvement of both areas may reflect a post-error cognitive response, where conflict between the executed and supposedly correct response occurs via the caudal ACC and LPFC. Based on experimenter observations in the current study, this interpretation seems likely as children sometimes showed a reaction reflecting conflict after making an incorrect button press in a no-go trial. Children would either verbally indicated that they made a mistake (e.g., saying "oh no") or show behavior of having committed an error (e.g., clasping hands over mouth, pulling hand away from keyboard).

Turning to schooling effects, P1 children showed greater improvements than KG children in vocabulary. The existing literature into whether and why schooling might improve vocabulary has been somewhat mixed. Morrison et al. (2019) conducted a review of the literature into schooling effects on vocabulary and found that three out of the five studies failed to find a positive effect of schooling. Further, the two studies that did find a positive effect either had higher program standards or a curriculum that emphasised greater vocabulary instruction. A potential reason for this discrepancy in findings might be related to family SES status. Wright and Neuman (2014) found that children from lower income schools encountered less opportunity for vocabulary learning. Specifically, the authors found that teachers from economically disadvantaged schools were less likely to discuss word meanings with children and also explained fewer challenging words. Consequently, children from lower income schools received only 60% of the vocabulary instruction provided to their more economically advantaged peers. This is important, as several studies have demonstrated that instruction aids children's vocabulary acquisition (Biemiller &

Boote, 2006; Kim, 2017) In the current study, parental education and income was above the national average, and thus, it is likely children were enroled into economically advantaged schools that provided a greater degree of instructional learning, leading to an improvement in vocabulary.

An interesting pattern of results also emerged in the brain activation data. Specifically, in the two frontal clusters identified from the response monitoring contrast, P1 children showed a greater difference in activation across time than KG children. We posit that, across the first school year, P1 children show stronger response monitoring due to the nature of the schooling environment. In school, emphasis is placed on instructional learning where children are provided with opportunities to engage in schoolwork and gain insights into their own performance based on teacher feedback (Denervaud, Knebel, et al., 2020). As this instructional learning takes hold, children learn to value correct answers and avoid errors (Denervaud, Knebel, et al., 2020). In contrast, the kindergarten environment introduces learning through more play-initiated activities (Morrison et al., 1997). While free play orientation may benefit children in many ways, it likely does not encourage the identification of errors on academic tasks as effectively as formal schooling (Denervaud, Knebel, et al., 2020).

To determine whether the larger activation difference in performance monitoring in the P1 children could predict academic performance, we investigated the longitudinal coupling between these variables. We found a positive trend between the change in activation in the left frontal cluster with performance on the math pack. This is in line with Kim et al. (2016) who found that stronger math skills (as well as reading skills) predicted stronger ERP component related to response monitoring. Further support for our finding stem from previous adult EEG research that found a larger ERN was significantly correlated with better academic performance as measured by student transcripts (Hirsh & Inzlicht, 2010). Given that monitoring one's own performance is a key aspect of self-regulation, the authors interpreted that individuals with a greater ability to monitor engage in self-regulatory behaviours that are important for academic success (Pintrich & De Groot, 1990). It is

however important to note that the change-change association between the left frontal cluster activation and math performance did not survive the formal model comparison. Therefore, the result needs to be interpreted with caution and stands for replication test. Future studies need to be better powered in terms of sample size. Hertzog et al. (2006) evaluated the statistical power of LCS models and found even with large sample sizes and multiple measurement occasions, statistical power to detect covariance in change remains low. Given the modest sample size of the present study coupled with the inclusion of only two measurement occasions, we likely did not have sufficient statistical power to detect meaningful relationships, even when present.

Finally, we found that for KG children only, those who began the study with better performance on the CDT task showed a greater increase in response monitoring activation across the year. We did not predict this result but it seems interesting, given that the KG children, at the mean level, did not show a significant change in activation difference across time. One interpretation for this finding relates to the interplay between children's individual characteristics and the schooling / kindergarten environment. We posit that the schooling environment may have facilitated all school children, regardless of their starting point, to become more sensitive to task accuracy and error, leading to a mean change in brain activation across the year associated with stronger response monitoring. On the other hand, for the reasons highlighted above, kindergarten children may encounter less explicit instruction. Only those who are already advanced at the start, presumably by eliciting more advanced interaction with adult caregivers, show a change in brain activation associated with more efficient response monitoring. Future studies should test this postulation by getting more direct measurement of social/instructional environment of children.

To conclude, the present study is the first to use a cut-off design to assess the impact of one year of schooling on both response inhibition and response monitoring and relate these differences to measures of academic achievement. No significant differences in response inhibition were found between the two groups of children. However, for response monitoring, after

one year of schooling P1 children showed a greater activation difference than KG children. Functionally, this activation difference was associated with better performance on the go/no-go task. When relating to broader measures of academic achievement, we found a positive trend between response monitoring and mathematical ability, preliminarily suggesting some functional relevance for school performance. Taken together, our findings highlight the role of the school environment in shaping the development of the neural network underlying monitoring of one's error.

CHAPTER 6 DISCUSSION AND CONCLUSIONS

This chapter will begin by summarizing the main findings from each of the experimental chapters and will then discuss the overall strengths and practical implications of the research. The limitations of this work will also be discussed and unanswered questions and recommendations for future research will be presented.

This PhD thesis sought to answer several questions pertaining to the development of WM and IC in four- to six-year-old children. Specifically, Chapters 2 and 4 examined which key factors contribute to individual differences in the development of pre-schoolers' VWM and IC and their neural correlates. Children were categorised into HP and LP groups based on their performance and group differences in brain activation were identified. Further, relationships between these performance-based differences in brain activation, child characteristics and environmental factors were investigated. Chapters 3 and 5 examined the longitudinal development of WM and IC and their neural correlates, and how these differ by the schooling experience. Further, the extent to which schooling-related changes in behaviour and/or brain activation underlying EF could predict academic outcomes over time was investigated.

6.1   Summary of thesis findings

6.1.1   Chapter 2

Previous research has shown individual differences in the development of WM are reliably predictive of future academic success (Bull et al., 2008; Swanson & Berninger, 1996) and cognitive function (Fukuda et al., 2010). These individual differences might stem from factors such as child temperament (Visu-Petra et al., 2018; Wolfe & Bell, 2004) and the quality of the home environment (Fishbein et al., 2019). However, previous research into individual differences in WM has primarily been behavioural and thus, neurodevelopmental investigations into individual differences in WM and underlying brain functions are lacking. Consequently, the nature of the relationships between behavioural

performance, brain function, child temperament, and the home environment are not well understood. Chapter 2 presents the first neuroscientific inquiry into individual differences in pre-schoolers' VWM processing using home-based testing. Specifically, this chapter investigated individual differences in 4.5-year-olds' VWM by examining the association between behaviour (measured using a colour change-detection task), brain activation (measured using fNIRS), and parent reported measures of the child's temperament and environment (measured using a battery of questionnaires).

Children were split into HP and LP groups based on their VWM capacity. A key finding was that LPs increasingly activated channels in the left frontal and bilateral parietal cortices with increasing load, whereas HPs did not show a difference in activation across load. This suggests that LPs recruited these areas to a greater extent when their VWM capacity was challenged. One interpretation of this result is that LPs needed to effortfully attend to the increasing demands of the task by increasing activation in the regions important for VWM processing. Another interpretation which stems from previous infant work (Wijeakumar et al., 2019) is that LPs were unable to suppress distracting or irrelevant information with increasing task demands, leading to an increase in activation. Another interesting finding was that HPs showed greater activation than LPs only at Load 1. This indicates HPs might have been more prepared from the outset, reaching a heightened state of attention resulting in greater activation at the start of the task. Further, HPs were likely more efficient at handling the demands of increasing load, and thus recruited similar levels of neural resources throughout the task.

The second critical question this chapter sought to answer was whether factors such as child temperament and the home environment could shed light on the nature of the individual differences in behaviour and associated brain activation. Results demonstrated a positive association between the number of stressful life events (measured as a greater number of stressful life events experienced by parents in their immediate family in the past 12 months including but not limited to, divorce, change in job/school, death of a family member, substance abuse) and activation in the left parietal cortex. Further, the

relationship between the frequency of stressful life events and poor task performance was mediated by activation in the left parietal cortex. One interpretation for this result is that instability in a child's life (resulting from a greater number of stressful life events) could result in changes in VWM processing. Specifically, in a household lacking in stability, children might be more distracted and struggle to sustain attention and efficiently maintain information. Further, parents experiencing a greater number of stressful life events might fail to fulfil daily goals and might transfer these poor goal maintenance skills to their children.

6.1.2   Chapter 3

Formal schooling begins at an age where rapid developments in EF are already taking place. While previous cross-sectional research has shown positive associations between schooling and WM skills (Roberts et al., 2015), more causal longitudinal investigations into schooling-related effects on WM are lacking. Further, there has been no research that has specifically investigated how schooling may impact the brain networks underlying WM. Thus, Chapter 3 aimed to fill in this knowledge gap and investigate whether the first year of formal schooling leads to improvements in VWM and its neural correlates and to relate these improvements to measures of academic success. Specifically, a modified school cut-off design was employed which allows for the comparison between two groups of children who are close in age but are enroled into different school years. Behavioural data was collected on a colour change-detection task and brain activation data was measured using fNIRS.

Results showed that across the year, children who attended one full year of schooling (P1) improved more in VWM than children who stayed in kindergarten (KG). Critically, P1 and KG children began the year with similar VWM, suggesting the improvements shown by the P1 children were due to exposure to formal schooling. One interpretation for this finding is that the school environment provided P1 children with more opportunities to improve their VWM skills, as factors such as remembering class rules, following

instructions, and engaging with academic materials all place a demand on WM skills (Alloway et al., 2009; Peng et al., 2016).

Another key finding was that P1 children showed greater improvements in vocabulary across the year than KG children. While the literature into schooling-related effects on vocabulary is mixed as to whether and how schooling might improve vocabulary, one interpretation is related to SES status. Previous research suggests children from high income schools receive more vocabulary instruction, as teachers are more likely to discuss word meanings with children and explain more challenging words (Wright & Neuman, 2014). Given that the overwhelming majority of P1 children were from high SES homes, it is likely they were enroled into economically advantaged schools that provided a greater degree of instructional learning, leading to an improvement in vocabulary. Lastly, P1 children who began the year with greater VWM skills gained more in vocabulary across the school year, likely due to the nature of the schooling environment. Specifically, schooling is a learning context that places a demand on WM in order for children to learn. Thus, children with better VWM at the start of the year are able to learn more across the year, and consequently, show greater improvements in vocabulary.

6.1.3 Chapter 4

IC is an essential cognitive skill with important implications for multiple aspects of development including academic achievement (Blair & Razza, 2007; Gawrilow et al., 2014; McClelland et al., 2014; Smith-Donald et al., 2007; Son et al., 2019) and psychosocial outcomes (Anzman-Frasca et al., 2015; Eisenberg et al., 2001; Rhoades et al., 2009; Shoda et al., 1990). Previous research into individual differences in IC development has suggested certain temperaments are positively associated with IC development (Wolfe & Bell, 2004) while certain environmental factors such as maternal exposure to stress / trauma during pregnancy have a negative effect on IC development (Bosquet Enlow et al., 2019). Response inhibition has been the focus of much research in children as several tasks, such as the go/no-go, can successfully measure

this construct across development. However, the literature surrounding the neural development of response inhibition in young children has proved contradictory, and thus, warrants further investigation. Chapter 3 therefore aimed to fill in the knowledge gap surrounding these issues and determine whether further insight into the neural pathways underlying response inhibition could be gained by probing individual differences, and related these differences to behaviour, child temperament, and home environmental factors. Specifically, this chapter investigated individual differences in 4.5-year-olds' IC by examining the association between behaviour (measured using a go/no-go task), brain activation (measured using fNIRS), and parent reported measures of the child's temperament and environment (measured using a battery of questionnaires).

Children were split into HP and LP groups based on their performance on the go/no-go task. A key finding was that LPs showed a greater difference in activation between go and no-go trials than HPs in channels overlying the bilateral frontal and parietal cortices. This is the first study into performance difference in this age group and thus the first to report this result, however, support for this finding stems from several adult studies that have reported larger electrical activity with increasing task difficulty (Band et al., 2003; Benikos et al., 2013; Jodo & Kayama, 1992). Thus, one interpretation for this finding is that LPs may have recruited these regions to a larger extent than HPs due to the increased strain on their inhibitory processes. Another interpretation is related to the type of task employed. The go/no-go task includes a WM component as children must hold a rule in mind while suppressing a prepotent response. Based on reports that suggest performance is negatively affected when the frontal cortex must perform multiple EFs (Luciana & Nelson, 1998), LPs here may have been inefficient at integrating the WM and inhibitory demands, resulting in poorer performance and consequently, increased brain activation.

Based on the observed group difference in brain activation, correlational analyses were run to investigate whether factors such as child temperament and home environment could shed light on the nature of the individual differences in response inhibition. However, no significant associations were

found. One interpretation for this finding is that individual differences in IC were not related to the measures of temperament and environment that were included here. Alternatively, the null result may be due to the high number of questionnaire variables that were included which had to be controlled for.

6.1.4 Chapter 5

Rapid development in children's EFs occur around the time they start formal schooling. In school, children are expected to exert greater control over their own thoughts and behaviours in accordance with their goals and context, drawing heavily on their cognitive control processes. Two aspects of IC that are often linked to academic success are response inhibition (Blair & Razza, 2007) and response monitoring (Denervaud et al., 2020; Kim et al., 2016). However, schooling-related effects into the neural pathways underlying these two processes and their relevance for predicting academic outcomes is yet to be investigated. Thus, Chapter 5 employed a modified school cut-off design to compare children who are close in age, but one group (P1) attended one full year of schooling while the other group stayed in kindergarten (KG). Behavioural data was collected using a go/no-go task and brain activation data was recorded using fNIRS.

Results showed no schooling-related effects in response inhibition. However, for response monitoring, P1 children showed a greater difference over time in activation between correct and incorrect responses in the bilateral frontal cortex than KG children. Further, greater response monitoring activation difference in the left frontal was related to better performance on the go/no-go task in both groups, in line with previous research relating more efficient response monitoring to a greater difference in activation between correct and incorrect responses (Grammer et al., 2014; Torpey et al., 2012). One interpretation for the group difference in activation is that P1 children show stronger response monitoring due to the nature of the schooling environment. While kindergarten initiates learning through play (Morrison et al., 1997), the schooling environment prioritises instructional learning where children engage

in schoolwork and gain insights into their own performance based on teacher feedback (Denervaud, Knebel, et al., 2020). Results also showed that the activation difference between correct and incorrect responses in the left frontal cortex showed a positive trend with mathematical ability for P1 children, suggesting there may be some functional relevance of response monitoring for academic performance.

Another key finding was that only KG children who began the year with better performance on the go/no-go task showed a greater increase in response monitoring related activation across the year. While this was not hypothesised, it might relate to the interplay between individual child characteristics and the schooling / kindergarten environment. Specifically, it may be that the schooling environment facilitated all school children (regardless of their starting point) to become aware of errors leading to a mean change in brain activation associated with response monitoring. However, as kindergarten children likely encounter less explicit instruction, only those who were already advanced at the start of the year showed a change in brain activation associated with more efficient response monitoring.

6.2 Strengths and practical implications of the thesis

This thesis has several strengths that warrant further discussion. First, all brain and behavioural data presented in this thesis were collected on children and their parents while in the comfort of their own homes. To ensure the home-based testing did not negatively impact the quality of the data collected, brain activity and behavioural performance on both the colour change-detection task (assessing VWM) and the go/no-go task (assessing IC) was compared to previous research. Specifically, in Chapters 2 and 3, VWM capacity was found to be comparable to findings reported by Simmering (2012). Further, analysis of the accompanying fNIRS data showed activity across the frontal and parietal regions, consistent with previous research assessing VWM in children using fNIRS (Buss et al., 2014; Tsujimoto et al., 2004). Chapters 4 and 5 replicated the behavioural patterns consistently reported by previous developmental

research using the go/no-go task, namely, greater accuracy for go than for no-go trials (Brod et al., 2017; Bunge et al., 2002). Additionally, analyses of the accompanying fNIRS data showed brain activity in the frontal and parietal regions, in line with previous fNIRS and fMRI research (Durston et al., 2002; Mehnert et al., 2013). Thus, this thesis demonstrates the feasibility of collecting neural data on children in a home-setting. This is important and raises the possibility for more inclusive developmental research to be conducted. While traditional laboratory testing allows for greater experimental control, some children may find the artificial and formal nature of these settings intimidating. Consequently, children with more fearful temperaments might not participate in the research, limiting the generalisation of findings. In the current thesis, children were tested in a familiar and comfortable environment, potentially allowing for the inclusion of individuals who otherwise might not be tested. This fact may have also played a role in accounting for the low drop-rate and low attrition across time, which is another strength of this research.

In total, 95 4.5-year-olds (P1 N=46; KG N=49) were recruited for this research. Sample size estimates were based on detecting group differences between P1 and KG children. Specifically, power analyses assuming a medium effect size (using estimates from Brod et al. (2017) and power of 0.95 suggested 32 participants per group would be sufficient for detecting a time by group interaction. This number was increased to 45 per group to prepare for attrition across time. A total of 15 children had to be excluded from data analysis in all chapters for refusing to participate at the first timepoint. Given the age range examined here in concert with the fact that brain activation data were collected, this is a relatively low number of children to be excluded. As proposed above, this is likely due to the fact that children were in a more comfortable environment than is afforded by laboratory experiments, allowing for a fun and engaging atmosphere where children did not feel they were being "tested". Further, when examining the longitudinal data, there was no attrition across time as all children and their parents who partook at the first timepoint agreed to take part the following year. This is a testament to the methodology employed here, as both children and their parents had a positive testing

experience and were happy to welcome the experimenters back into their homes.

The research presented in Chapters 3 and 5 suggests the schooling experience affords some improvements in cognitive function and underlying brain activity which has practical implications for parents. Specifically, the arguments presented in Chapter 3 detail how the school environment directly leads to improvements in VWM. Further, evidence presented in Chapter 5 demonstrates that schooling has a positive impact on the brain networks underlying successful response monitoring. These findings are important as many parents of children born in January and February struggle to decide whether to enrol or defer their child's entry to school. Particularly in the U.K, where the school entrance age is among the lowest in Europe (Sharp, 2002), some parents are fearful that entering their children into school at this age will have negative consequences for their development. In addition to the benefits in VWM and response monitoring associated with the first year of school, the current research did not find any adverse consequences to starting school at 4.5-years-old. Thus, these findings can provide some reassurance to parents who want to enrol their children as soon as they are eligible. However, it is important to note these reassurances are only applicable in the context of the EF processes measured here and that these findings must not be overextended. Specifically, the current research did not compare longitudinal growth exhibited by children who enrol into school early versus those who enrol one year later, and thus, is unable to provide evidence either for or against early versus late enrolment.

Finally, this study demonstrates the potential for cognitive neuroscience to detect the effects of an intervention (i.e schooling) before these effects are evident in behaviour (Gabrieli et al., 2015). Specifically, findings presented in Chapter 5 showed that, although there were no differences in task performance, children who attended one year of schooling (compared to children who stayed in kindergarten) showed a neural response in the frontal cortex associated with better response monitoring. Further, a positive trend was found between brain activity associated with response monitoring and

mathematical ability, suggesting some functional relevance of response monitoring for academic performance. Thus, by collecting brain activation data in addition to behavioural data, the current thesis could detect schooling-related effects that otherwise would not have been identified. This has practical implications for researchers and policy makers who wish to evaluate the effectiveness of educational interventions.

6.3 Limitations of the thesis

A limitation of this research is related to the recruitment strategy employed here. Specifically, the study information was sent to gateway organisations such as schools, nurseries, and leisure centres. Interested parents then got in touch with the research team who went over the criteria for inclusion. If eligible parents / children met the criteria, a testing session was scheduled. Consequently, this strategy may have led to a volunteer bias. Rosenthal (1965) published an extensive review of the literature and found that in general, volunteers for research tended to be female, well educated, and from higher social class, to name a few. These characteristics ring true for the current research, as parental educational attainment and income was above average. Specifically, 95% of children had at least one parent who had attained a BSc degree or higher. Further, the net annual household income of this sample was higher than the national average. This may be one reason why the research conducted in Chapters 2 and 4 could not replicate the associations between EF and SES that have been consistently reported in the literature (Hassan et al., 2019; Maguire & Schneider, 2019; Sarsour et al., 2011; St. John, Finch, et al., 2019; St. John, Kibbe, et al., 2019; Wijeakumar et al., 2019; Xing et al., 2019). Further, given that the dataset used across all chapters did not include families from lower SES backgrounds, the findings presented here cannot be generalised to children from lower SES homes. While this is a limitation of the current research, efforts were made to recruit a more diverse sample. A list of all nurseries and primary schools across central Scotland, both private and public, was compiled. These organisations were contacted and leaflets containing the study information were mailed to those that agreed to display

these outside their classrooms. Further, a small gift and remuneration was advertised, and members of the research team carried out presentations across several locations to encourage participation in these areas.

Another potential limitation might be related to the modified school-cut off design employed here. In traditional school cut-off designs, children whose birthdates fall shortly before and shortly after an arbitrary cut-off date are compared. Thus, the allocation of children into each experimental group is relatively arbitrary. On the other hand, the current research recruited children born only in January and February of one year, as regulations in Scotland permit parents of children born in these months to decide whether to enrol or defer their child's entry to school. Thus, the decision is ultimately left to the parents, who presumably make this decision based on whether they believe their child is ready for school. Thus, it is possible that children who were enroled into school were fundamentally different than children who remained in kindergarten. While this is a consideration that must be taken into account, it is important to note that no differences in performance were found between P1 and KG children at the first timepoint on any of the tasks including WM, IC, numeracy and vocabulary. In addition, more pointedly, no differences emerged between P1 and KG children at the first timepoint in any of the parental questionnaires. This is important, given that the present research included a broad range of questionnaires measuring child temperament, quality of the parent-child relationship, and a range of environmental factors including SES, level of disorganisation in the home, and number of daily hassles experienced by parents. This is interesting, as it suggests parents might not accurately perceive whether their child is ready for school. In other words, if parents who chose to enrol their children were doing so because they believed their child was academically advanced and thus ready for school, P1 children should have performed better in the tasks at the first timepoint. Alternatively, if parents who chose to enrol their children were doing so because their child was socially ready for school, P1 children should have scored lower on temperamental factors such as hyperactivity and higher on factors such as conduct problems, to name a few. However, the absence of any group differences at the first

timepoint suggest parental beliefs concerning school readiness are not reflected in the quantitative measures of cognitive function, academic performance and temperament included here.

6.4 Unanswered questions and recommendations for future research

Each chapter contained in this thesis furthers our understanding of the topics addressed here while simultaneously opening new doors for future research. For instance, Chapter 2 reports several key findings furthering our understating of the neural networks underlying individual differences in VWM performance. Specifically, LP children showed greater modulation in activation across load when their capacity limits were challenged, suggesting greater neural effort was required with increasing task difficulty. However, as the HP children performed well throughout the task, their capacity limits were not challenged, and they showed no modulation in activation across load. To confirm this interpretation, future work should include a load 4, to investigate whether the HPs would begin to show the same neural pattern as the LPs (namely, a significant difference in activation between load 1 and load 4) when their VWM capacity is challenged. Chapter 4 reported similar results when examining performance on a go/no-go task. Specifically, LPs on this task also showed greater difference in activation between go and no-go trials than HPs, suggesting greater neural effort was required to complete the task. However, this chapter failed to associate these differences with any temperamental or environmental factors. This may have been due to the number of questionnaires employed, leading to a high number of tests that had to be controlled for. Future research should craft a more focused research question to probe which factors contribute to the individual differences in response inhibition. Specifically, factors which have been most commonly associated with response inhibition in the literature include temperament (as assessed here using the SDQ + PSI), parenting factors (assessed here using the PSI), and SES (assessed here using SES scale). A priori limiting the investigation to including only the variables of most interest

could further our understanding of the factors which might contribute to the observed differences in neurocognitive function.

While the current research has provided evidence for schooling-related improvements in EF and its neural correlates, it is unknown whether the KG children here would show the same longitudinal change as the P1 children when they begin school. This leads to an interesting question; would the KG children (due to being one year older when they start school) show *more* progress during their first year of school than the P1 children? It should be noted that the current research was initially proposed to run over the course of three years, from 2018 to 2020. However, due to the COVID-19 pandemic, the last timepoint of data could not be collected in participant's homes. Further, due to the multiple lockdowns, schools were closed for a portion of the year causing a disruption in children's traditional learning setting. Thus, even if it had been possible to collect the data from children in their homes during the summer of 2020, the disrupted school experience would have confounded the research. Future research is therefore needed to include this third timepoint of data so that the longitudinal growth in EF shown by the P1 children during their first year of school can be compared to the longitudinal growth in EF shown by the KG children during their first year of school. Any potential differences in the mean change shown by each group could signify a benefit of either early school entrance or late school entrance. Most of the research examining the impact of delaying school entry has been conducted in the U.S. and has focused on how this impacts academic performance. For instance, Zill et al. (1997) conducted a large-scale survey comparing children who were "retained" as a result of teacher recommendations and academic performance with children who were "held back" from starting school by their parents – a process termed "redshirting" in the U.S. While these researchers did find gender and ethnic differences between the groups, the survey did not identify any advantages or disadvantages associated with delayed school entry based on parental reports of children's' progress in first and second grade. It is important to note however, that any positive or negative effects of early versus late school entrance may only emerge later in development. For instance, while some research suggests

being the oldest in the class leads to social and academic benefits in the first three years of schooling (Spitzer et al., 1995; West et al., 2000), others report these benefits are short lived and may even be disadvantageous in the long-term (Byrd et al., 1997).

Finally, future research should also identify which classroom variables specifically drive the schooling-related improvements in EF reported here. Previous work by Sharp (2002) identified several ways in which the schooling environment might differ from kindergarten. For instance, children in school spend less time on tasks of their own choosing as schoolteachers take on a more instructive and didactic role than kindergarten teachers. Children in school also spend less time outside exploring their environments and engaging in physical activity, and more time indoors sitting still in classroom settings. Further, the school curriculum places a larger emphasis of learning subject-specific academic material while kindergarten emphasizes learning through play. Similarly, Morrison et al. (2019) published a review of studies examining the causal impact of schooling on literacy and highlighted several factors that are crucial to understanding schooling-related effects on learning. These included foundational aspects of the classroom such as the structural organisation of the classroom (class size, teaching qualifications), the quality of the classroom environment (teacher warmth, classroom organisation) as well as instructional factors such as subject specific content, specific aspects of that content, the setting (whole class vs small group), and who is focusing the child's attention to learning (teacher, peer, alone). Morrison et al. (2019) argues these factors operate simultaneously and predict more of the variability in student outcomes than any individual construct. Future research is needed to determine, which, and to what extent, these variables might contribute to the schooling-related improvements in EF reported in this thesis.

6.5 Conclusion

This thesis investigated the factors which contribute to individual differences in the neurocognitive development of two types of EF, namely WM and IC, in a

sample of four- to six-year-old children. Using a portable fNIRS machine, home assessments of WM and IC were collected on children across two years. Further, academic assessments and parent-reported measures of the child's temperament and environment were collected. This research also employed a school cut-off design, so that schooling-related differences in EF and their potential for predicting academic outcomes over time could be investigated.

The novel research presented in this thesis furthers our understanding of individual differences in EF and underlying brain function. By contributing to our understanding of how the schooling environment shapes the neurocognitive development of EF, this thesis hopes to provide parents who struggle to decide whether to enrol their children into school with reassurances regarding the schooling experience. More generally, this thesis demonstrates the potential for cognitive neuroscience to be applied in early development to identify changes due to schooling before these changes are evident in behaviour (Gabrieli et al., 2015). This is an important lesson for researchers and policy makers who wish to assess the effectiveness and developmental implications of schooling-related interventions.

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APPENDIX A: UNIVERSITY OF STIRLING'S GENERAL UNIVERSITY ETHICS PANEL APPROVAL (375)

UNIVERSITY *of*
STIRLING

Eva Rafetseder
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20 March 2018

General University Ethics Panel (GUEP)
University of Stirling
Stirling
FK9 4LA
Scotland UK

E: GUEP@stir.ac.uk

Dear Eva

Re: Ethics Application: *SAND-Dissociating the Effects of Age and Schooling Across Neurocognitive Development-* **GUEP375**

Thank you for your submission of the above to the General University Ethics Panel.

I am pleased to confirm that GUEP has approved your application, and you can now proceed with your research.

The panel has asked that to provide a respons to the following points so that the information can be held on file:

- In the inclusion criteria number 3 Did your child have a normal term (37 - 42 weeks), uncomplicated birth? [yes] Does this just mean a normal birth or does it include uncomplicated forceps or caesarean birth also.
  Yes, we will include cases using uncomplicated forceps and caesarean births.
- Inclusion criteria 5 – earlier criteria refer to 'your child' while 5 changes to – 'do any of the parents…' is this a bit odd in wording?
  We have changed it to "Do you or the child's mother and father (depending who is on the phone) have any major psychiatric or depressive illness"

Please ensure that your research complies with Stirling University policy on storage of research data http://www.stir.ac.uk/is/researchers/data/afteryourresearch/

Please note that should any of your proposal change, a further submission (amendment) to GUEP will be necessary. If you have any further queries, please do not hesitate to contact the Committee by email to guep@stir.ac.uk.

Yours sincerely,
Pp

Edna S. Dockely

On behalf of GUEP
Professor Helen Cheyne
Deputy Chair of GUEP

The University of Stirling is a charity registered in Scotland, number SC 011159.

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APPENDIX B: QUESTIONNAIRE SUBSCORES

Table B1. List of questionnaires and 31 corresponding subscores. Descriptions and ratings for each subscore are included. For the VWM task, each subscore was correlated with HbO difference in activation measures in the left frontal, right parietal, and left parietal. For the IC task, each subscore was correlated with HbO difference in activation measures in the right frontal, left frontal, right parietal, and left parietal. *Socioeconomic Scale included additional variables that were not entered into further analyses.

| Questionnaires									
Strengths and Difficulties Questionnaire		Parent Daily Hassles		Confusion, Order, and Hubbub Scale		Parenting Stress Index		Socioeconomic Scale*	
Subscores	Description and Rating	Subscores	Description and Rating	Subscore	Description and Rating	Subscores	Description and Rating	Subscores	Description and Rating
Emotional Problems	5 items (i.e complains, unhappy) Higher score = more emotional problems	Challenging Behaviour	7 items (i.e whining, interuptting) Higher score = child displays more challenging behaviour	Total Score	15 items (i.e rushing, regular routine) Higher score = more chaos	Child - Hyperactivity	9 items (i.e distracted, active) Higher score = more hyperactive	Parent Education	Highest qualification achieved Higher score = higher education
Conduct Problems	5 items (i.e temper, fights) Higher score = more conduct problems	Parenting Tasks	8 items (i.e errands, cleaning) Higher score = parent experiences more parenting tasks			Child - Reinforces Parent	6 items (i.e smiling, appreciated) Higher score = child does not reinforce parent	Parent Annual Income	Annual income after taxes Higher score = higher income
Hyperactivity	5 items (i.e restless, fidgeting) Higher score = more conduct problems	Frequency	Frenquency of challenging behaviour + parenting tasks Higher score = higher frequency			Child - Mood	5 items (i.e cries, fusses) Higher score = more moody	Parental Aspirations	Highest qualification parent hopes child achieves Higher score = higher aspirations
Peer Problems	5 items (i.e solitary, picked on) Higher score = more peer problems	Intensity	Intensity of challenging behaviour + parenting tasks Higher score = higher intensity			Child - Acceptability	7 items (i.e learning, ability) Higher score = child's characterisitcs don't match parent expectations		
Prosocial	5 items (i.e kind, helpful) Higher score = more prosocial					Child - Adaptability	11 items (i.e overreacts, clingy) Higher score = child is more difficult to manage		
Difficulties	Sum of emotional problems, conduct problems, hyperactivity and peer problems					Child - Demandingness	9 items (i.e cries, interrupts) Higher score = child presents more behavioural problems that demand attention		
Externalising	Sum of conduct problems and hyperactivity					Parent - Competence	13 items (i.e doubts, decision making) Higher score = parent feels less		
Internalising	Sum of emotional problems and peer problems					Parent - Attachment	7 items (i.e guilt, closeness) Higher score = parent less attached to child		
Impact	Impact the difficulties have on everyday life Higher score = higher impact					Parent - Role Restriction	7 items (i.e control, responsibilities) Higher score = parent feels more trapped by being a parent		
						Parent - Depression	9 items (i.e depression, guilt) Higher score = parent feels more depressed		
						Parent - Parenting Partner Relationship	7 items (i.e relationship problems, conflict) Higher score = worse partner relationship		
						Parent - Isolation	6 items (i.e lonely, friendships) Higher score = parent feels more isolated		
						Parent - Health	5 items (i.e aches, sleep) Higher score = parent experiences poorer health		
						Life Stress	19 items (i.e divorce, death) Higher score = parent experiences more life stress		

APPENDIX C: HbR ANOVA RESULTS FOR THE VISUAL WORKING MEMORY TASK (TIMEPOINT 1)

Table C1. Channels showing significant interactions between load and chromophore and group, load and chromophore. Posthoc results are shown for HbR activation.

Channel No.	Brain Area (MNI coordinates)	Load x Chromophore (HbR)	Group x Load x Chromophore (HbR)
Channel 1	Right middle frontal gyrus		
Channel 2	Right middle frontal gyrus		
Channel 3	Right inferior frontal gyrus		
Channel 4	Right inferior frontal gyrus		
Channel 5	Left middle frontal gyrus		
Channel 6	Left middle frontal gyrus		
Channel 7	Left inferior frontal gyrus	Load 1 > Load 3 ($p = 0.028$)	
Channel 8	Left inferior frontal gyrus		
Channel 9	Right angular gyrus		Load 1: LP > HP ($p = 0.014$)
Channel 10	Right superior occipital gyrus		
Channel 11	Right supramarginal gyrus		Load 1: LP > HP ($p = 0.013$)
Channel 12	Left inferior parietal lobule		Load 1: LP > HP ($p = 0.018$) LPs: Load 1 > Load 3 ($p = 0.046$)
Channel 13	Left angular gyrus		
Channel 14	Left supramarginal gyrus		

APPENDIX D: CORRELATIONS BETWEEN BRAIN AND BEHAVIOUR FOR THE VISUAL WORKING MEMORY TASK (TIMEPOINT 1)
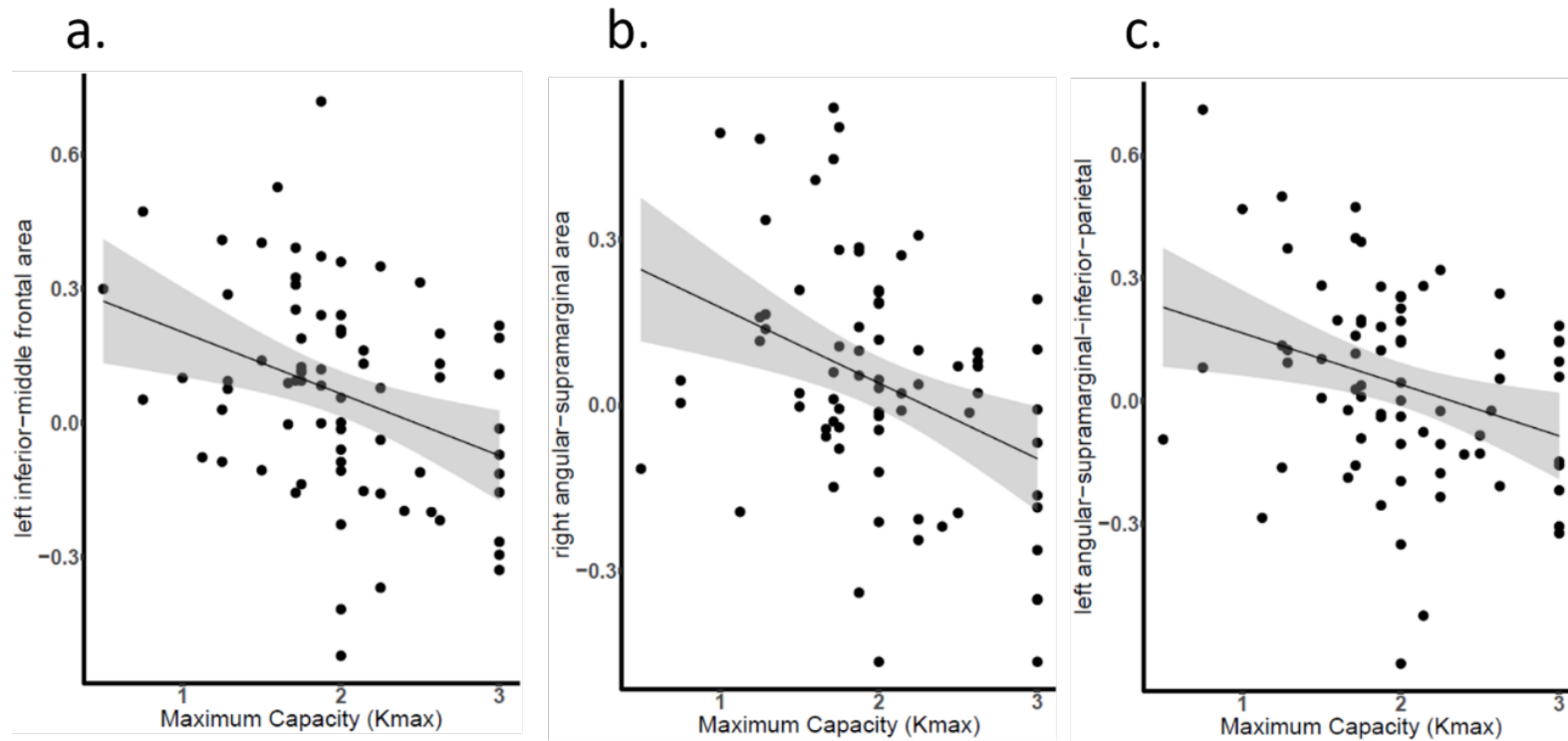
Figure D1. (a) Correlation plots between maximum capacity estimates and HbO difference in activation measures for the left inferior-middle frontal area, **(b)** right angular-supramarginal area, and **(c)** left angular-supramarginal-inferior-parietal area.

APPENDIX E: UNIVERSITY OF STIRLING'S GENERAL UNIVERSITY ETHICS PANEL APPROVAL (375A)

UNIVERSITY of STIRLING

Eva Rafetseder
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03 July 2019

General University Ethics Panel (GUEP)
University of Stirling
Stirling
FK9 4LA
Scotland UK

E: GUEP@stir.ac.uk

Dear Eva,

Re: Ethics Application: *SAND-Dissociating the Effects of Age and Schooling Across Neurocognitive Development-* **GUEP375A**

Thank you for submitting the revisions to your submission of the above to the General University Ethics Panel. The ethical approaches of this project have now been reapproved by GUEP.

Please note that should any of your proposal change, a further submission (amendment) to GUEP will be necessary.

Please ensure that your research complies with the University of Stirling policy on storage of research data which is available at:
https://www.stir.ac.uk/about/faculties-and-services/information-services-and-library/current-students-and-staff/researchers/research-data/plan-and-design/our-policy/

If you have not already done so, I would also strongly encourage you to complete the Research Integrity training which is available at: https://canvas.stir.ac.uk/enroll/CJ43KW

If you have any further queries, please do not hesitate to contact the Panel by email to guep@stir.ac.uk.

Good luck with your research.

Yours sincerely,
Pp.

On behalf of GUEP
Dr William Munro
Deputy Chair of GUEP

APPENDIX F: HbR ANOVA RESULTS FOR THE INHIBITORY CONTROL
TASK (TIMEPOINT 1)

Table F1. Channels showing significant interactions between trial type and
chromophore. Posthoc results are shown for HbR activation.

Channel No.	Brain areas (MNI coordinates)	Group x Trial x Chromophore (HbR)
Channel 1	Right middle frontal gyrus	
Channel 2	Right middle frontal gyrus	
Channel 3	Right inferior frontal gyrus	LP: No-go > Go (p = 0.029)
Channel 4	Right inferior frontal gyrus	
Channel 5	Left middle frontal gyrus	LP: No-go > Go (p = 0.028)
Channel 6	Left middle frontal gyrus	
Channel 7	Left inferior frontal gyrus	
Channel 8	Left inferior frontal gyrus	LP: No-go > Go (p = 0.028)
Channel 9	Right angular gyrus	
Channel 10	Right superior occipital gyrus	
Channel 11	Right supramarginal gyrus	
Channel 12	Left inferior parietal lobule	LP: No-go > Go (p = 0.038)
Channel 13	Left angular gyrus	
Channel 14	Left supramarginal gyrus	LP: No-go > Go (p = 0.006)

APPENDIX G: HbR ANOVA RESULTS FOR THE INHIBITORY CONTROL TASK (TIMEPOINT 1 AND TIMEPOINT 2)

Table G1. Channels showing significant interactions between trial type and chromophore. Posthoc results are shown for HbR activation.

Channel No.	Brain areas (MNI coordinates)	Trial x Chromophore (HbR)
Channel 1	Right middle frontal gyrus	No-go > Go ($p = 0.043$)
Channel 2	Right middle frontal gyrus	
Channel 3	Right inferior frontal gyrus	
Channel 4	Right inferior frontal gyrus	
Channel 5	Left middle frontal gyrus	
Channel 6	Left middle frontal gyrus	
Channel 7	Left inferior frontal gyrus	
Channel 8	Left inferior frontal gyrus	
Channel 9	Right angular gyrus	
Channel 10	Right superior occipital gyrus	
Channel 11	Right supramarginal gyrus	
Channel 12	Left inferior parietal lobule	
Channel 13	Left angular gyrus	
Channel 14	Left supramarginal gyrus	No-go > Go ($p = 0.01$)

Table G2. Channels showing significant interactions between trial type and chromophore and group, trial type and chromophore. Posthoc results are shown for HbR activation.

Channel No.	Brain areas (MNI coordinates)	Trial x Chromophore (HbR)	Group x Time x Chromophore (HbR)	Group x Trial x Time x Chromophore (HbR)
Channel 1	Right middle frontal gyrus			P1 No-go: T2 > T1 (p = 0.028) No-go T2: P1 > KG (p = 0.045)
Channel 2	Right middle frontal gyrus			No-go T1: KG > P1 (p = 0.048)
Channel 3	Right inferior frontal gyrus			
Channel 4	Right inferior frontal gyrus			P1 Go: T1 > T2 (p = 0.046) P1 No-go: T2 > T1 (p = 0.038)
Channel 5	Left middle frontal gyrus			
Channel 6	Left middle frontal gyrus			
Channel 7	Left inferior frontal gyrus			
Channel 8	Left inferior frontal gyrus	No-go > Go (p = 0.045)		
Channel 9	Right angular gyrus		KG: T1 > T2 (p = 0.047)	
Channel 10	Right superior occipital gyrus			
Channel 11	Right supramarginal gyrus			
Channel 12	Left inferior parietal lobule			
Channel 13	Left angular gyrus			
Channel 14	Left supramarginal gyrus	No-go > Go (p = 0.042)		