# Neurobehavioral precursors of executive function in early development

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# Abstract

Executive Function (EF) refers to an interrelated set of neurocognitive systems that underlie behavioral control and cognitive flexibility. EF has pervasive influences on cognition and later development. Previous studies have highlighted that there is a great deal of EF development that goes on from the preschool period through adolescence. In recent years, there has been a growing interest in exploring how executive functions develop in the first three years of life. The present thesis aims to contribute to this literature by exploring how early attentional control, in the form of attentional orienting and executive attention, and working memory interact and co-develop to support forms of complex functioning with an eye toward understanding how EF develops at two levels: brain and behavior. Importantly, we used tasks that rely on looking measures so this line of research can be scaled down to see if/how these skills are related to the emergence of EF from infancy to early childhood. In study 1, we found evidence that attentional control is related to executive control in children aged 24-72 months. In study 2, we replicated these findings, showing that attentional control is related to executive control in toddlers and young children. Critically, our results provide evidence that measures of basic visual dynamics relate to longitudinal changes in cognitive development and executive control. Consistent with previous research, we found task-relevant brain activity among WM and attention tasks in canonical WM and attentional networks. Importantly, there was overlap in the spatial localization of these activation patterns which is consistent with the idea that WM and attention share neural correlates early in development.

Moreover, these activation patterns were predictive of later executive control and may serve as biomarkers of emerging cognitive control. Our results set the stage for future work to measure looking dynamics in infancy to predict longer-term executive control outcomes. This work furthers our understanding of how changes in brain function lead to specific developmental cascades from 30- to 42-months.

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# Chapter 1

# Introduction

## 1.1 Development of Executive Function

Infancy and toddlerhood are a time of rapid change in the organization of cognition and behavior. Importantly, the brain undergoes a great deal of development and reorganization during this period. What is less understood are the mechanisms by which these brain changes support behavioral development. This research project is interested in exploring the early precursors of executive function (EF) at two levels, brain and behavior. In particular, this research traces the early development of attentional control and working memory with an eye toward understanding the early development of EF.

There are multiple ways to carve up executive functions. A dominant account is to think of executive function and control in terms of the integration of multiple component systems (Miyake et al., 2000). From this perspective, EF refers to an interrelated set of neurocognitive systems that underlie behavioral control and cognitive flexibility critical for adaptive functioning. EF has been shown to be reliably predictive of language development (Im-Bolter, Johnson, & Pascual-Leone, 2006; Mcevoy, Rogers, & Pennington, 1993), mathematical abilities (Bull & Scerif, 2001) and measures of general cognitive functioning (e.g., school performance, IQ, and psychopathology; Liss et al., 2001; Pennington & Ozonoff, 1996). Furthermore, poor EF, or executive dysfunction, has been implicated in a number of childhood disorders such as attention-deficit/hyperactivity disorder, autism and conduct disorders (Casey, Thomas, Davidson, Kunz, & Franzen, 2002), and poor EF is associated with a variety of adverse adjustment outcomes (see Blair & Razza, 2007; Hughes & Ensor, 2011; Moffitt et al., 2011; Ozonoff & Jensen, 1999; Shoda, Mischel, & Peake, 1990). Thus, understanding the development of EF has broad implications and may be critical to intervention efforts with at-risk children.

The emergence of cognitive and behavioral control remains a topic of continuous study. Many studies have explored the development of EF from preschool to adulthood; and previous studies have highlighted that there is a great deal of development that goes on in the preschool period through adolescence (Blakemore & Choudhury, 2006; Luna et al., 2001). More recently, EF has been investigated in progressively younger children. Some efforts have been made into exploring how infant and toddler cognitive abilities relate to later, more complex forms of EF (see Fiske & Holmboe, 2019; Hendry, Jones, & Charman, 2016; Perry, Swingler, Calkins, & Bell, 2016; Cuevas & Bell, 2014). A primary challenge in attaining a clear picture of how EF develops is its multi-component nature.

EF is composed of inhibition, working memory, and cognitive flexibility (Friedman & Miyake, 2017; Collette et al., 2005; Davidson, Amso, Anderson, & Diamond, 2006; Garon, Bryson, & Smith, 2008; Lehto, Juujärvi, Kooistra, & Pulkkinen, 2003; Miyake et al., 2000). These components are still-developing (and are not yet stable) throughout childhood. Each one of these abilities show non-linear changes in early development resulting in a complex set of developmental cascades across cognitive domains. Significant changes in social, motor, and language development are also evident during this period; thus, it is particularly challenging to disassociate the different components of EF and create 'pure' measures that are age-appropriate and predictive of later development.

From middle childhood to adulthood, executive functions show a pattern described as 'unity and diversity' (Friedman & Miyake, 2017; Miyake et al., 2000), that is, EF is composed of functionally distinct cognitive abilities that generally operate in conjunction in order to carry out certain tasks. This pattern is less evident in young children. Contradictory accounts have suggested, on one hand, that preschool EF is best characterized by a single, unitary factor (Hughes & Ensor, 2009; Senn, Espy, & Kaufmann, 2004; Wiebe, Espy, & Charak, 2008; Wiebe et al., 2011; Willoughby, Wirth, & Blair, 2012) while more recent studies have reported dissociable EF factors in toddlers and preschoolers (Bernier, Carlson, Deschênes, & Matte-Gagné, 2012; Garon, Smith, & Bryson, 2014; Mulder, Hoofs, Verhagen, van der Veen, & Leseman, 2014; Skogan et al., 2016) , thus supporting the 'unity and diversity' pattern that is present in adults. For instance, Garon et al. (2014) introduced a novel battery to measure EF in children aged 18 months to 5 years. The battery included measures of working memory, inhibition, and task shifting. Using a structural equation model, they reported that working memory and shifting load onto separate disassociable factors of EF. These individual factors also load into a unitary 'common EF' factor. Interestingly, they reported that simple and complex forms of inhibition did not load into a disassociable factor but to the common EF factor. They interpreted this as suggesting that inhibition is part of a more mature/complex collection of abilities which make up the common EF factor. Further supporting the multi-factor nature of EF, a factor analytic study of the Behavior Rating Inventory of Executive Functions (BRIEF-P) also reported a multi-factor structure of preschool EF (Skogan et al., 2016).

EF components have been shown to emerge in different contexts across development. For example, rudimentary forms of inhibition have been shown in infancy using the A-not-B paradigm (e.g., Thelen, Schöner, Scheier, & Smith, 2001) and the Tongue task (e.g., Kochanska, Murray, & Harlan, 2000; Wolfe & Bell, 2007) while more complex forms are evident during early childhood in the day-night task (e.g., Gerstadt, Hong, & Diamond, 1994), Simon task (Gerardi-Caulton, 2000), flanker task (e.g., Rueda et al., 2004), Stroop task (e.g., Carlson, 2005), and Go/No-Go task (e.g., Fishburn et al., 2019; Cragg & Nation, 2008; Dowsett & Livesey, 2000). Increases in working memory capacity have been studied in infancy and toddlerhood using preferential looking tasks (e.g., Ross-Sheehy & Eschman, 2019; Ross-Sheehy, Oakes, & Luck, 2003; Oakes, Hurley, Ross-Sheehy, & Luck, 2011; Oakes, Ross-Sheehy, & Luck, 2006) and in preschoolers using change detection tasks (e.g., Simmering, 2012; Buss, Fox, Boas, & Spencer, 2014) and spatial working memory tasks (e.g., Perlman, Huppert, & Luna, 2016). Moreover, capacity estimates derived from infant looking tasks and adult-like change detection tasks have been studied in preschoolers using behavioral, modeling, and neuroimaging techniques (Simmering, 2016; Delgado Reyes, Wijeakumar, Magnotta, & Spencer, in prep) which shed light onto the basic processes that support WM in each of these task-specific contexts. Finally, cognitive flexibility, or switching, has been studied with toddlers using single-rule categorization-like tasks (Carlson, Mandell, & Williams, 2004) and later on with more complex tasks that require switching between rule sets (Brace, Morton, & Munakata, 2006; Buss & Spencer, 2014; Müller, Gela, Dick, Overton, & Zelazo, 2006; Zelazo et al., 2003).

The regulation of emotional responses, often dubbed effortful control or 'hot' EF, develops in conjunction with 'cool' EF processes named above and shows incremental development throughout childhood (Hill, Degnan, Calkins, & Keane, 2006; Lamm & Lewis, 2010; Posner, Rothbart, Sheese, & Voelker, 2012). Together, they can be thought of as self-regulatory constructs which have been shown to be strongly associated and overlapping despite their different theoretical groundings (Bridgett, Oddi, Laake, Murdock, & Bachmann, 2013; Tiego, Bellgrove, Whittle, Pantelis, & Testa, 2019).

The pervasive influence of EF over development has led researchers to investigate links between early behavioral markers and the emergence of EF. Indeed, the development of these self-regulatory functions have been theorized to rely on basic cognitive functions such as attention (Colombo & Cheatham, 2006; Garon et al., 2008; Rueda, Posner, & Rothbart, 2011; Hendry et al., 2016; Holmboe, Bonneville-Roussy, Csibra, & Johnson, 2018; Ruff & Rothbart, 1996).

Based on these results, early measures of attention could potentially be used as an early indicator of children at-risk for EF deficits. Furthermore, early emerging individual differences in attentional control and working memory, a known subcomponent of EF, may play a role in mediating later-developing differences in academic and other forms of learning (Wass, Scerif, & Johnson, 2012). Therefore, in the present study I asked: can we look at early attentional control and working memory with an eye to understanding how EF develops?

### 1.1.1 Role of Attentional Control

Attention has been theorized as a subset of networks that subserves a variety of attentional processes (Petersen & Posner, 2012). According to this perspective, attention is composed of three networks: alerting, orienting, and executive. These subsystems develop at different rates and have been thought to subserve a variety of cognitive processes.

The capacity to exert attentional control, that is, the ability of an individual to choose what to pay attention to and what to ignore, is thought to emerge towards the end of the first year as the neural correlates of such systems mature (Wass et al., 2012; Deoni et al., 2011; Gordon et al., 2011; Johnson et al., 2010). These abilities continue to develop slowly relative to exogenous, stimulus-driven, forms of attention which have been shown to be relatively mature early on (Iarocci, Enns, Randolph, & Burack, 2009). Importantly, attentional control processes, involved in the inhibition sub-component of executive function, are thought to exert influence over the functioning of other executive domains (Anderson, 2002). Indeed, this cognitive system is thought to be a 'hub' cognitive ability, that is, a domain-general faculty important for the acquisition of skills across a variety of domains (Wass et al., 2012; Cornish, Cole, Longhi, Karmiloff-Smith, & Scerif, 2012; Cornish, Steele, Monteiro, Karmiloff-Smith, & Scerif, 2012; Scerif, 2010). In all, the ability to regulate attention results in the child being able to actively guide their attention to information-rich areas that facilitate learning (Ruff & Rothbart, 1996; Scerif, 2010) and inhibit attention to irrelevant stimuli.

Previous studies have argued that orienting and sustained attention serve as a foundation for the development of goal-directed self-regulatory behaviors (Garon et al., 2008; Rothbart, Derryberry, & Posner, 2004). For instance, individual differences in orienting and sustained attention have been shown to correlate with later forms of attention as well as more complex forms of cognition (Ruff, 1990). Additionally, in a recent study, Posner, Rothbart, Sheese, and Voelker (2014) reported that the earliest forms of self-regulation in infancy depend on the orienting attentional network. In contrast, Colombo and Cheatham (2006) have argued that endogenous, non-reactive, forms of attention serve as the foundation of executive functioning.

Work from Blankenship et al. (2019) has shown that infant attention at 5 months is predictive of EF at 10 months, as measured by a looking A-not-B task, with EF going on to show a continuous development from 10 months to 6 years. Together, these data provide evidence that infant attention is associated with early childhood EF. Interestingly, Rothbart and colleagues failed to find an association between 6- to 7-month-olds' reactive and anticipatory looks in a sequential looking task, and executive attention at 3–4 years of age (Posner et al., 2012; Rothbart, Sheese, Rueda, & Posner, 2011). They later reported that anticipatory looking was related to orienting at 4- and 7- years of age (Posner et al., 2014).

Several tasks use infants' orienting responses as a measure of attentional and neural development. The Gap Overlap task, for example, assesses the infant's ability to disengage from a salient central attractor in favor of a peripheral target (Elsabbagh et al., 2009; Holmboe et al., 2010; Johnson, Posner, & Rothbart, 1991). Previous work has used this type of task to measure different components of visual orienting in early infancy: the ability to disengage from one stimulus to attend another, the ability to show anticipatory looking, and the ability to use a cue to predict the spatial location of a subsequent target. They reported that 4-month-olds–and not 2- or 3-month-olds–were able to disengage and learn the contingency. They also reported that the 4-month-olds showed more anticipatory looks than the younger groups. To asses visual orienting proficiency, Ross-Sheehy, Schneegans, and Spencer (2015) developed the Infant Orienting With Attention (IOWA) task. This task relies on spatial cueing effects to measure infant's ability to covertly shift attention and to make fast and accurate eye movements to the target. Critically, the task provides measures of functionally and neurally distinct aspects of attention.

The neural underpinnings of attention have been studied from very early stages of development to aging. Posner et al. (2012) have shown that even in neonates, parietal cortex shows strong connectivity to lateral/medial frontal areas previously implicated in attentional processes and EF (Posner, Rothhart, Sheese, & Tang, 2007; Gao et al., 2009; Rothbart & Posner, 2006; Rothbart, Sheese, & Posner, 2007). Further, behavioral and imaging studies have shown substantial development in attentional networks between infancy and early childhood (Posner et al., 2007).

Attentional orienting has been shown to involve frontal eye fields (FEF) and areas of bilateral superior and inferior parietal lobe (Rueda, Pozuelos, & Combita, 2015). Executive attention, on the other hand, is subserved by the cingulo-opercular network (Neta, Nelson, & Petersen, 2016). However, early on, there is significant overlap between the orienting and the executive attentional networks (Gao et al., 2009). Specifically, researchers have reported that there is strong functional connectivity between the parietal areas (associated with the orienting network) and the lateral and medial frontal areas (associated with the executive network).

Notably, Conejero, Guerra, Abundis-Gutiérrez, and Rueda (2018) reported that the executive network, which has been shown to have protracted development, is present in infancy. In particular, they show that areas activated by error detection in infants are similar to those activated by adults, including the anterior cingulate cortex (ACC). However, evidence from Posner et al. (2014) suggests that connectivity between these regions and regions that control motor output are not functionally efficient until 4 years. It is important to note that while these attention networks are anatomically distinct, they interact functionally to support optimal performance (Xuan et al., 2016; Mullane, Lawrence, Corkum, Klein, & McLaughlin, 2016).

Developmental studies have shown that functional activity in these networks is related to temperament measures of self regulation (Posner et al., 2014; Rothbart et al., 2011). Sophisticated forms of attention and rudimentary forms of emotional regulation emerge during the first year of life as significant development occurs in the neural processes thought to underlie attention (Colombo, Harlan, & Mitchell, 1999; Grolnick, McMenamy, & Kurowski, 2006; Posner & Fan, 2008). Better attention performance has been related to higher EEG power, specifically higher 6.8 Hz alpha synchronization, at fronto-central and parietal locations in 7- to 12-month-old infants (Orekhova, Stroganova, & Posikera, 2001). Higher baseline EEG power for the 6–9Hz frequency band at all scalp locations and larger baseline to task increases in the same index for frontal locations, have been associated with longer looking on visual habituation tasks (Diaz & Bell, 2011) and better performance on WM tasks that rely on shifting attention (Bell, 2002; Bell & Wolfe, 2007; Cuevas & Bell, 2011). Additionally, Perry et al. (2016) reported that greater EEG power at medial frontal locations (particularly for right frontal location) during an attention task was associated with observed attentional behavior. Thus, evidence from EEG has posited medial frontal regions as important correlates of early attentional behaviors.

### 1.1.2 Role of working memory

Another cognitive system that is thought to play a key role in cognition is working memory (WM). WM is a core cognitive system with a highly limited capacity. WM capacity limitations are reliably associated with individual differences in a wide variety of cognitive functions (Conway, Kane, & Engle, 2003), and WM deficits have been observed in clinical populations, including children diagnosed with attention- deficit/hyperactivity disorder and autism, as well as children born preterm (Jiang, Capistrano, & Palm, 2014; Willcutt, Doyle, Nigg, Faraone, & Pennington, 2005; Steele, Minshew, Luna, & Sweeney, 2007; Vicari, Caravale, Carlesimo, Casadei, & Allemand, 2004).

Basic forms of working memory have been shown to be present by 8-months of age and continue to develop throughout infancy (Diamond, 1985), toddlerhood, and the preschool period. More complex WM skills emerge in early childhood and continue to specialize during the adolescence period (Luciana & Nelson, 1998; Gathercole, Pickering, Ambridge, & Wearing, 2004; Luna, Garver, Urban, Lazar, & Sweeney, 2004). Neuroimaging studies have identified the frontoparietal network as playing a central role in working memory (Wager & Smith, 2003; Owen, McMillan, Laird, & Bullmore, 2005; Rottschy et al., 2012). Studies with children have identified the lateral prefrontal cortex as an important region that supports WM development (Perlman et al., 2016).

One particularly important component of the WM system is visual working memory (VWM). VWM plays a critical role in normal processing of the visual world by supporting the comparison of objects that cannot be simultaneously foveated and detecting changes when they occur. VWM capacity has been shown to correlate highly with many aspects of cognition including general fluid intelligence (Fukuda, Awh, & Vogel, 2010).

VWM develops rapidly during the first year of life (Ross-Sheehy & Eschman, 2019; Oakes et al., 2006; Ross-Sheehy et al., 2003). Its reliance on visual dynamics opens doors to use indices of this cognitive system to inform theories of WM development and may serve as an early marker for later neurocognitive capabilities. As reviewed in Buss, Ross-Sheehy, and Reynolds

(2018), studies in infancy have shown that from 6- to 12-months there is substantial increase in VWM capacity using preferential looking tasks (Oakes et al., 2006; Oakes, Messenger, Ross-Sheehy, & Luck, 2009; Ross-Sheehy et al., 2003), increased ability to bind features to locations across different task contexts (Kaldy & Leslie, 2003; Káldy & Leslie, 2005; Oakes et al., 2006, 2009), and improved performance in the A-not-B task (Cuevas & Bell, 2010; Hofstadter & Reznick, 1996). Beyond infancy, in the context of the change-detection task, children's VWM capacity continues to develop from 1.5 objects at age 3 to adult-like estimates by age 7 (Riggs, Simpson, & Potts, 2011; Simmering & Patterson, 2012; Simmering, 2016; Simmering & Miller, 2016). In a recent study, Ross-Sheehy and Eschman (2019) used looking dynamics and pupilometry results to show that infant and adult mechanisms of change-detection may be qualitatively similar by 11 months of age.

Several studies have explored the neural correlates of WM in early development. For instance, Short et al. (2013) reported a positive relationship between infants performance in a visuospatial working memory task and indices of white matter integrity in white matter tracts connecting brain regions thought to support WM (for related findings using resting-state fMRI see Alcauter et al., 2015). In an EEG study, Cuevas, Bell, Marcovitch, and Calkins (2012) reported that changes in frontal coherence and power in the 6–9 Hz frequency band predicted improvements in VWM performance at 10 months of age, but not earlier in development. In a neuroimaging study in 7- to 22-year-olds, Kwon, Reiss, and Menon (2002) showed incremental WM-related activity over development within a fronto-parietal network that included left and right dorsolateral prefrontal cortex (DLPFC), left posterior ventrolateral prefrontal cortex (VLPFC), and left and right posterior parietal cortex (PPC). Moreover, Geier, Garver, Terwilliger, and Luna (2008) showed that task-specific WM networks are engaged by 8 years of age. This network includes frontal eye fields (FEF) for shifts of attention, as well as left superior parietal lobule (SPL) and right superior frontal gyrus (SFG) for maintenance of items in VWM. They also found that intraparietal lobule (IPL) and middle frontal gyrus (MFG) contributed to maintenance functions in childhood when the task was increasingly difficult. Notably, the inferior frontal gyrus (IFG) showed increases in activation from childhood to adolescence with a decline into adulthood suggesting an improvement in neural efficiency late in development (for related results, see Scherf, Sweeney, & Luna, 2006). Recent work using a change detection task with 3- and 4-year-olds found increases in left parietal and left frontal activation as the VWM load was increased from 1 to 3 items, as well as an increase in parietal activation from 3 to 4 years (Buss et al., 2014).

Delgado Reyes, Wijeakumar, Magnotta, Forbes, and Spencer (in rev) used behavioral and neuroimaging methods to probe the development of VWM from 4 months to 2 years. In the study, infants and toddlers (4mo-2yo) completed a preferential looking task (Ross-Sheehy et al., 2003) and, in a separate study, preschoolers (3.5- and 4.5-yo) complete both a change detection task (Simmering & Patterson, 2012) and the aforementioned preferential looking task while recording functional near-infrared spectroscopy (fNIRS) data. Results showed an overall increase in mean look durations as the set size increased, as well as a decrease in the rate of shifting back-and-forth between displays. Thus, with more items, children's attention to each display was heightened. The primary developmental trend was a significant increase in change preference (CP) scores between 4 months and 2 years when children had to remember one item (set size 1 or SS1). Interestingly, many 3 and 4yo's showed a familiarity bias at SS1, demonstrating discrimination of the displays as in Simmering (2016) but the opposite looking pattern. To help place the PL findings in context–particularly the interesting effects with 3 and 4yo's–it is useful to examine behavioral performance from the second task, change detection. As expected, max K–the standard measure of WM capacity used in adult studies–was higher for 4yo (M=2.09, SD=0.61) than 3yo (M=1.84, SD=0.62), but this difference was not significant (consistent with Simmering, 2016).

The results show early changes in frontal cortex that are followed by changes in visual processing and attention areas and, later, by changes in WM processes in parietal cortex. Results showed robust correlations between the two tasks, replicating empirical and modeling findings from Simmering (2016). Moreover, fNIRS findings localized areas in the brain—most notably, L-MFG—that subserve VWM functions in both tasks. These data are important in that they link measures of early neurobehavioral function with good predictors of childhood and adult productivity and success (Max *K*). fNIRS results show a clear cascade of developmental effects early in development, as well as emerging functionalities at 3 and 4 years localized in frontal cortex. Taken together, these data provide evidence that areas of frontal, parietal, and temporal cortex are involved in VWM throughout early childhood into adolescence.

### 1.1.3 Present study

Cognitive control has been historically associated with neural networks involving the prefrontal cortex (Baddeley, 1986; Duncan, Emslie, Williams, Johnson, & Freer, 1996; Duncan, Johnson, Swales, & Freer, 1997; Norman & Shallice, 1986). However, recent work has shown that EF is not localized in the prefrontal cortex; rather, it emerges from dynamic interactions within an extensive network that includes frontal and posterior cortical regions (Fiske &

Holmboe, 2019; Dosenbach et al., 2007; Fair et al., 2007; Morton, 2010). Furthermore, this network undergoes major changes over development including changes in functional connectivity and activation dynamics (Barnea-Goraly et al., 2006; Buss & Spencer, 2014; Crone, Wendelken, Donohue, & Bunge, 2006; Fair et al., 2007; Gogtay et al., 2004; Lenroot & Giedd, 2006; Moriguchi & Hiraki, 2009; Sowell, Trauner, Gamst, & Jernigan, 2002; Stevens, Kiehl, Pearlson, & Calhoun, 2009; Tsujimoto, 2008). Therefore, EF emerges as a result of the development and re-organization of complex neural networks throughout the brain.

Recent work has explored the mechanisms that underlie the development of early cognitive abilities and how they might relate to incremental development of executive control (Cuevas & Bell, 2014; Fiske & Holmboe, 2019; Holmboe et al., 2018). The present study builds on this work by exploring how early forms of attention and WM are related to concurrently, and later developing, executive control skills. I included measures of both effortful control and executive functions in order to elucidate relationships among 'hot' and 'cool' domains.

This study is unique in two ways. First, it focused primarily on attention and WM as key sub-components of EF. Second, it used tasks that have proven to be robust to measure cognitive abilities in infancy. I used tasks that rely on eye movements as dependent measures. This is a very simple response that would allow us to eventually tap the cognitive systems of interest at younger ages. Thus, by using tasks that rely on visual dynamics, we can use the same paradigm across a large age range without having to assume similarities across tasks that differ in infancy versus early childhood.

In chapter 2, the goal is to examine whether attention and WM as measured in looking tasks predict concurrent EF in 24-72mo. If so, this sets the stage to explore the neural bases of these components in chapter 3. This also sets the stage for a key long-term goal: to deploy these tasks and neuroimaging tools to examine the development of these EF subcomponents in infancy with an eye toward predicting EF from infancy through toddlerhood.

The structure of the thesis is as follows. In chapter 2 I first examined which eye-movement measures are linked to EF in childhood in a large age-range developmental cohort. The primary questions of this chapter are as follows: How do EF components develop from 24mo-6yo? How are these components related and how do these relationships change over development? Finally, how do attentional control and working memory interact and co-develop to support concurrently developing forms of EF?

In Chapter 3, I provide a look at the neural processes that underlie the early development of EF abilities using converging behavioral and neuroimaging techniques. Previous work has shown that attentional control and WM have overlapping neural correlates (Duncan & Owen, 2000; Munakata et al., 2011), particularly early in development (Astle & Scerif, 2009; Scherf et al., 2006; Shing, Lindenberger, Diamond, Li, & Davidson, 2010; Velanova, Wheeler, & Luna, 2008). In this chapter, I build on this work to explore if the component abilities of WM and attention rely on overlapping neural systems at 30 months and if individual differences in WM and attention at the behavioral and neural level related to the emergence of later developing EF skills. By combining indices of brain function with behavioral measures, I elucidate relationships between functional activity and behavioral performance that shed light into the early processes that underlie later, more complex forms of EF.

Finally, chapter 4 integrates the findings from the previous chapters and what they contribute to our understanding of EF development. Future directions and limitations of this work are discussed.

# Chapter 2

# The co-development of WM, Attention, and EF in a cross-sectional sample

## 2.1 Introduction

Executive function (EF) refers to an interrelated set of cognitive abilities that underlie behavioral control and cognitive flexibility critical for adaptive functioning. It has been widely studied across development and shown to be reliably predictive of long-term cognitive and social developmental outcomes (Im-Bolter et al., 2006; Mcevoy et al., 1993; Bull & Scerif, 2001; Liss et al., 2001; Pennington & Ozonoff, 1996). Thus, understanding the development of EF has broad implications and may be critical to intervention efforts with at-risk children.

Recent work has explored the mechanisms that underlie the development of early cognitive abilities and how they might relate to the incremental development of executive control (Cuevas & Bell, 2014; Fiske & Holmboe, 2019;

Holmboe et al., 2018). Rudimentary forms of cognition such as attention serve as building blocks of executive function (Hendry et al., 2016). Additionally, the development of working memory has been shown to be a fundamental process in emerging complex cognitive abilities (Cowan, 2014). Indeed, evidence suggests that early emerging individual differences in attentional control and working memory may play a role in mediating later-developing differences in academic learning (Wass et al., 2012).

The present study builds on this work by exploring how early forms of attention and WM relate to concurrently developing EF skills. We included measures of both effortful control and executive function in order to elucidate relationships among 'hot' and 'cool' executive abilities. The goal of study 1 was to explore the development of EF subcomponents in a large range developmental cohort. I chose to focus on attentional control and working memory given their pervasive influence across a variety of domains of cognitive development. Further, these components can be measured very early in development, opening up the possibility of extending this work to infancy to elucidate how early cognitive components relate to later EF longitudninally.

An important aspect of the present study is that I used tasks that rely on eye movements as the dependent measure. This is a very simple response that would allow us to eventually tap the cognitive systems of interest at younger ages. In particular, I used a battery of tasks that included measures of executive attention and orienting attention, including a modified version of the procedure in Johnson et al. (1991) to measure anticipatory looking and disengagement. Importantly, this paradigm has been used with infants as young as 2 months which is consistent with my goal of using these measures very early in development. Additionally, I used the Infant Orienting with Attention task from Ross-Sheehy et al. (2015). This paradigm provides measures of visual spatial attention and saccade planning by including similar characteristics (e.g., alerting, congruency) as those found in the attentional network test (ANT; Rueda et al., 2004).

To measure working memory, I used two paradigms that rely on change preference: the Visual Working Memory-Preferential Looking task (VWM-PL; Ross-Sheehy et al., 2003) and the Looking Change Detection task (VWM-4Sq; Ross-Sheehy & Eschman, 2019). Additionally, the 'cool' EF outcome measure was the Minnesota Executive Function task (MEFS; Carlson & Zelazo, 2014). To measure 'hot' EF, or effortful control, participants completed the Gift Wrap and Gift Delay task (Kochanska & Kim, 2014) and parents completed the age-appropriate version of the child behavioral questionnaire (ECBQ; Putnam, Gartstein, & Rothbart, 2006) or (CBQ; Rothbart, Ahadi, Hershey, & Fisher, 2001).

I traced out developmental changes in each of the tasks and then explored, using path analysis, how these abilities are related in early development. In sum, the primary goal of this chapter is to explore which eye-movement measures are linked to EF in childhood. I investigated the development of EF components in a large age-range developmental cohort. In particular, I elucidate how EF components interact and co-develop to support concurrent EF from 24mo-72mo. Figure 2.1 shows the theoretical model behind this work. Particularly, the figure shows a theoretical model of the relationship across rudimentary forms of WM (VWM) and attention (orienting and executive attention) and how these co-develop with and support executive function and effortful control over the course of development. The primary questions of this chapter are how attentional control and working memory develop from 24mo-72mo, how these candidate EF components are related, how these relationships change over development, and whether these components predict concurrent EF and effortful control.

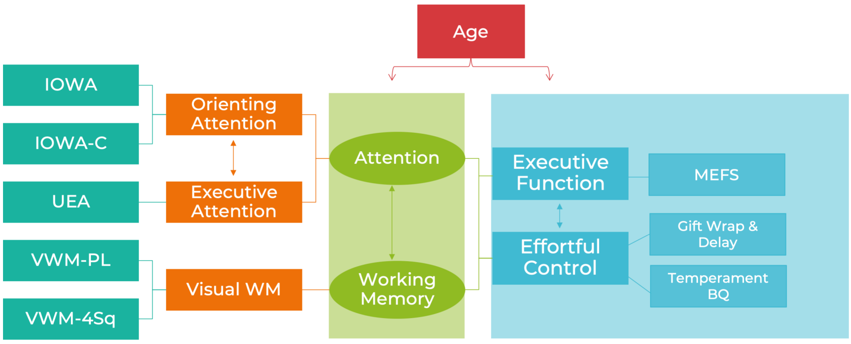

Figure 2.1: Theoretical model of relationships between basic cognitive abilities and EF. Circles show theorized latent variables and squares show observed/measured variables.

## 2.2 Methods

### 2.2.1 Participants

The final sample included 130 children aged 24- to 72-months-old (*M* = 46.5 months, *SD* = 12.8 months, 66 female). Age distribution is shown in Figure 2.3. Participants had normal or corrected-to-normal vision. Color vision was explored using a parent questionnaire developed by Ross-Sheehy to probe for a family history of color blindness. An additional 17 children were recruited to participate in the study but were not included in final analysis due to fussiness (3), did not provide enough useable data (e.g., had noisy eye tracking data, 14). Figure 2.2 shows the distribution of data by each task.

Table 2.1 shows the sample demographics. Children were 85.4% white, 4.6% asian, and 3.1% mixed race. 69.3% of mothers had completed a Bachelor's degree or higher. Mean family annual income ranged from £36,400 to £51,999.

This project was reviewed and approved by the Ethics committee at the

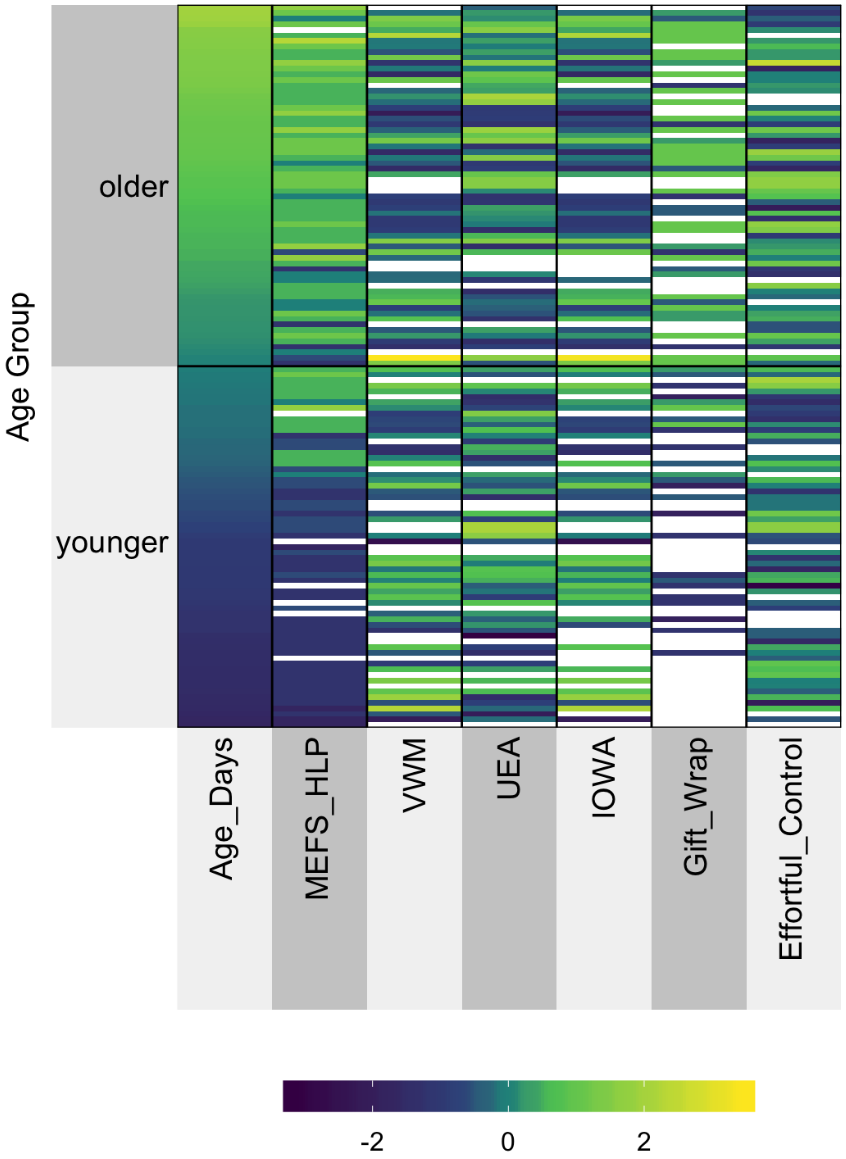

Figure 2.2: Data across tasks for each participant. Participants are median split for visualization purposes (median = 1408.5 days). White portions depict missing data. Every row is a child. Row-by-row participant data is scaled and color coded such that higher values are shown in lighter colors. For instance, darker blue in the Age_Days column reflect younger kids, while greener colors reflect older kids. Moreover, performance across tasks is similarly depicted, with greener colors meaning higher scores, and thus, better performance.

| **Sample Demographics; overall n = 130** | |
|---|---|
| **Age in Months** | |
| Mean (SD) | 46.5 (12.8) |
| Median [Min, Max] | 46.5 [24.0, 72.0] |
| **Ethnicity** | |
| African | 1 (0.8%) |
| Asian | 6 (4.6%) |
| Mixed | 4 (3.1%) |
| White | 111 (85.4%) |
| Missing | 8 (6.2%) |
| **Parent 1 Education Status** | |
| GCSE/O levels equivalent | 9 (6.9%) |
| A levels or equivalent | 13 (10.0%) |
| Trade apprenticeship | 2 (1.5%) |
| some university | 8 (6.2%) |
| Bachelor's Degree | 56 (43.1%) |
| Master's Degree | 17 (13.1%) |
| Doctorate or Professional Degree | 17 (13.1%) |
| Missing | 8 (6.2%) |
| **Parent 2 Education Status** | |
| Left School | 2 (1.5%) |
| GCSE/O levels equivalent | 10 (7.7%) |
| A levels or equivalent | 12 (9.2%) |
| Trade apprenticeship | 15 (11.5%) |
| some university | 9 (6.9%) |
| Bachelor's Degree | 46 (35.4%) |
| Master's Degree | 11 (8.5%) |
| Doctorate or Professional Degree | 13 (10.0%) |
| Missing | 12 (9.2%) |

Table 2.1: Summary of sample demographics.

University of East Anglia. Parents signed an informed consent form. Children received a small toy of their choosing and a t-shirt for participating. The data reported here are a subset of a larger study examining the early precursors of executive function.

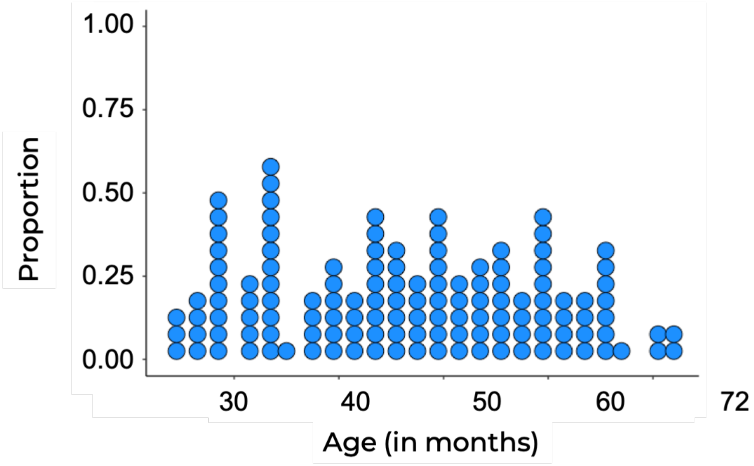

Figure 2.3: Age distribution.

### 2.2.2 Procedure

Participants completed a battery of task that tap attention, working memory, effortful control, and executive function. The sample included participants as young as 2-year-olds and as old as 6-year-olds. In order to overcome the limitations posed by young toddlers limited abilities, I used tasks that used eye movements as dependent measures. This is a very simple response that would allow us to eventually tap the cognitive systems of interest at younger ages. Critically, this also allowed the use of the same tasks across a large age range.

For all eye-tracking tasks (attention and working memory tasks, see details below), a 42-inch LCD television that was connected to a PC running SR Research Experiment Builder was used to display the stimuli. Participants were seated on their caregivers lap or on a high chair approximately 100 cm from screen. The eye tracker was an Eye-Link 1000 plus (SR Research, Ontario, Canada) in the remote setting. The eye tracking camera was placed on a small stand at a distance between 600 - 700mm from the participant.

A small target sticker was placed on participants' foreheads which allowed tracking of head (and eye) position even when participants moved or the pupil image was lost. The eye-tracker was set to monocular recording such that it tracked the gaze position of a single eye using pupil and corneal reflections of an infrared light source. The sampling rate was 500 Hz. As part of the set-up there were two additional cameras in the room, one located beside the eye tracking camera which recorded the participant's face, and one located in the ceiling at the back of the room to record the experiment as it was presented on the monitor.

The experiment began with a short clip of *Elmo's World* (Sesame Street). While this video played, the experimenter placed the small target sticker on the participants' forehead. Once the target sticker was in place, the tracking camera was adjusted so the distance from target to camera was approximately 650mm. After checking that the pupil and corneal reflection were visible on the camera, the calibration procedure began. During calibration, participants were shown a looming black and white geometric shape in five locations of the screen (middle, top, bottom, left, right) used to map raw eye position data to the camera image data and thereby allowing mapping of gaze position to the stimulus presentation. Following successful calibration, the experiment commenced. This calibration procedure took place before all eye-tracking tasks described below.

#### 2.2.2.1 Working Memory

Participants completed one of two visual working memory tasks: Visual Working Memory — Preferential Looking (VWM-PL; Ross-Sheehy et al., 2003) or Looking Change Detection (VWM-4Sq; Ross-Sheehy & Eschman, 2019). Previous work from our lab had used the VWM-PL task with infants and young children. However, there is some evidence that the paradigm might not be ideal to measure 3- and 4-year-olds' working memory. At the time this project started, Ross-Sheehy et al. had a second looking-based change detection task in development; thus half the sample completed the VWM-PL and half completed the VWM-4Sq with the goal being to examine whether one task is more predictive of EF than the other.

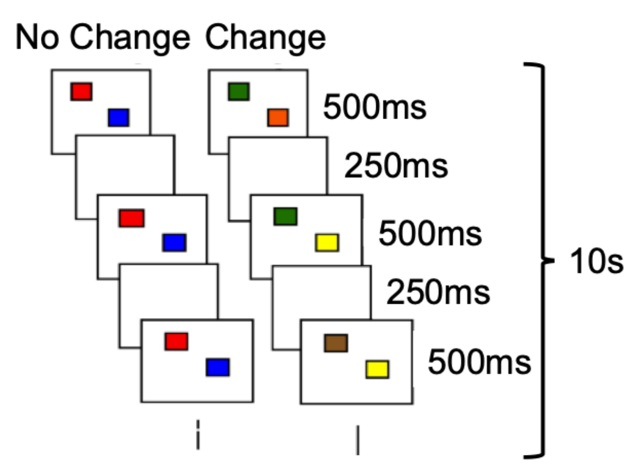

Figure 2.4: Trial schematic for the VWM-PL task.

**2.2.2.1.1 Visual Working Memory — Preferential Looking (VWM-PL)** I used a modified version of the task introduced by Ross-Sheehy et al. (2003). On each trial participants saw two side-by-side flickering displays composed of an array of colored squares. One side contained the change display and the other contained the no-change display. Each display contained colored squares that measured approximately 5 cm (w) by 5 cm (h). The set size (SS; number of items in each array) was the same between the two displays and remained constant during the 10s trials. The colors of the squares were randomly selected from a set of nine colors: green, brown, black, violet, cyan, yellow, blue, red and white. The colors on a display were always different from each other but colors could be repeated between the displays (i.e., the same color could appear on both displays). The squares simultaneously appeared for 500ms and disappeared for 250ms. For the no-change display, the colors of the squares remained constant throughout the length of the trial. For the change display, one of the squares changed color after each delay. The changing square was randomly selected, and its color was derived from the set of colors not currently present in that display. Set size (2, 4 , 6) and change side (left, right) were tested within subjects, resulting in 6 unique trial types. These trials were presented randomly within each block for up to 6 blocks (36 trials max; 12 of each SS), or until children lost interest or became fussy. The displays containing the colored squares were 21cm (h) by 29.5cm (w) in projected size, separated on the screen by 21 cm, and subtended an average visual angle of 13.7 degrees. Figure 2.4 shows a schematic of a SS2 trial.

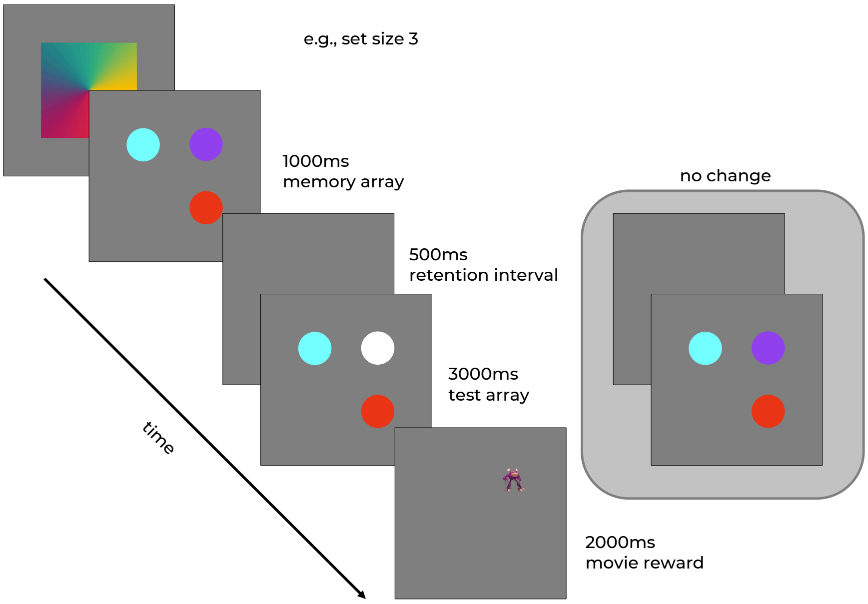

Figure 2.5: Trial schematic for the 4-Square change detection task.

**2.2.2.1.2 Looking Change Detection task** Participants completed the looking change-detection paradigm (VWM-4Sq) from Ross-Sheehy and Eschman (2019). This paradigm consisted of a 1000 ms sample array comprised of 1–4 colored circles, followed by a 500 ms retention interval, and a 3000 ms test array that was either the same as the sample array (no-change trials), or one of the items changed in color (change trials). The location of the circles were determined pseudo-randomly, with the contingency that circles be contiguous in either the horizontal or vertical plane. The location of the changed item was set pseudo-randomly for each trial. After the test array, children saw a 3s audiovisual animation in the location where the change had occurred (animated creature dancing to music). Each trial began with a dynamic audiovisual fixation stimulus (a musical spinning color-wheel). Set size (1–4 circles) and condition (change, no-change) were tested within subjects, resulting in 8 unique trial types. These trials were presented randomly within each block for up to 6 blocks (48 trials max), or until children lost interest or became fussy. The colored circles were 10cm (h) by 10cm (w) in projected size, separated on the screen by 10.5 cm, and subtended an average visual angle of 5.7 degrees. Figure 2.5 shows a schematic of a SS3 trial.

#### 2.2.2.2 Attention

**2.2.2.2.1 Infant Orienting with Attention task (IOWA)** The IOWA task follows the procedure described in Ross-Sheehy et al. (2015). The trial commenced with a central fixation, or attention getter (AG), in the form of a brightly colored dynamic zooming square animation. The trial commenced with the attention getter appearing centrally until the participant fixated on it. This was followed by a precue interval of 200ms which was then followed by the target stimuli. The target stimuli could appear to the left or right of the AG and remained on screen for 3000ms. The spatial precue was a small black circle and the target images were images of everyday objects. The precue was 1cm in projected size and subtended a visual angle of 0.6 degrees. The target

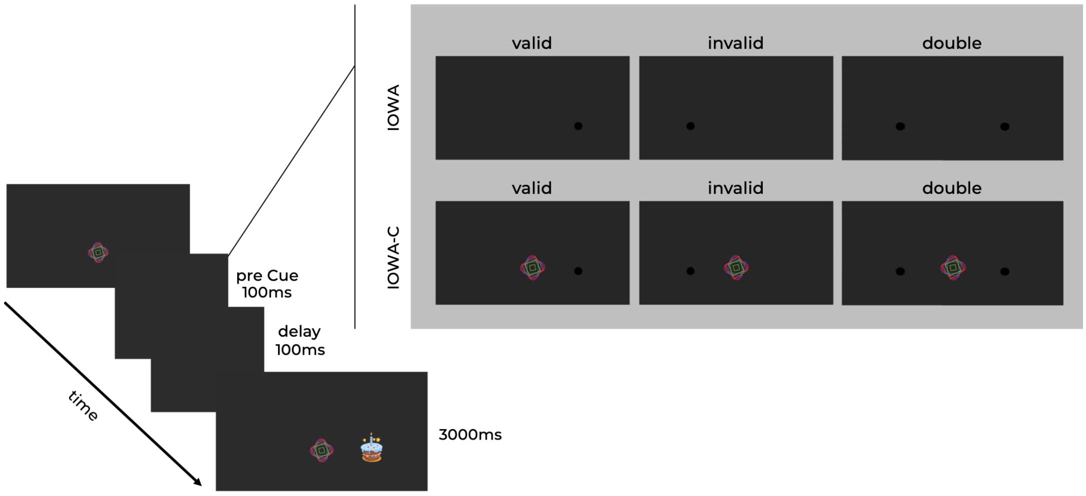

Figure 2.6: Trial schematic for the IOWA task. The sequence shows a IOWA: control trial. On the top right, all other possible trial types are shown. During IOWA-C trials, the sequence of the trial is the same except the attention getter remains on the screen for the entire duration of the trial.

images were between 5 and 7 cm in projected size and subtended an average visual angle of 3.4 degrees. The attention getter was 8cm in projected size and subtended a visual angle of 4.58 degrees. The distance between attention getter and target image was 25 cm.

There were three experimental conditions which contained a 100-ms spatial precue. The cues could appear (1) in the same location of the target (valid cue), (2) contralateral to the target (invalid cue), or (3) on both sides (double cue). An additional manipulation included competition (or overlap; IOWA-C) trials, which consisted of the same experimental conditions but the central fixation stayed on during the length of the trial. This introduced competition between the attention getter and the target object. Reaction times and directional looking were recorded for each trial. Figure 2.6 shows a schematic of all possible conditions during the task.

**2.2.2.2.2 Unified Executive Attention (UEA)** The Executive Attention task largely follows the procedure described in Johnson et al. (1991). Each trial

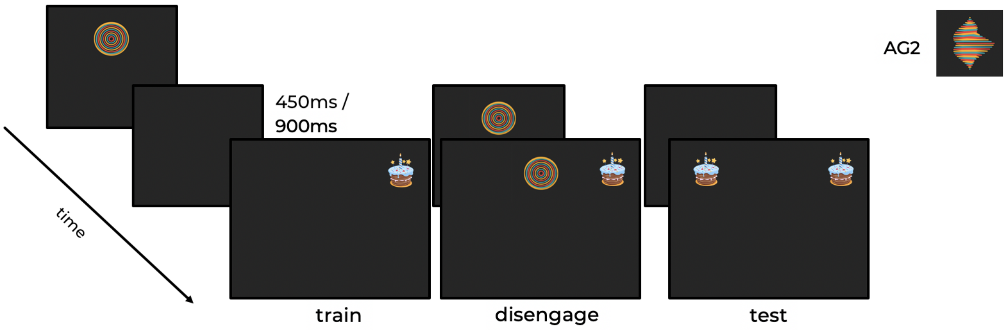

Figure 2.7: Trial schematic for the UEA task.

begins with a centrally positioned attention getter (AG). One of two AG stimuli appeared in a pseudo randomized sequence. The AGs were two distinct brightly colored animated gifs accompanied by distinct auditory stimuli. Trials commenced when the participant fixated on the AG. There were three types of trials: training trials, test trials, and disengage trials. On training trials, the AG went away immediately after the fixation. There was a 450ms (during the training phase; first 18 trials) or 900ms gap (during test) preceding the target onset, after which the target stimulus appeared to the left or right side of the AG. The AG presented at the beginning of the trial was predictive of the location of the target (left or right). The target stimuli were everyday objects (e.g., cake, balloons). On test trials, the target appeared on both sides of the screen regardless of which of the two AGs preceded it. Disengage trials were similar to training trials but the AG stayed on throughout the trial. This resulted in an overlap trial where the contingent relationship between AG-target remained intact but both stimuli (i.e., AG and target) were presented simultaneously. Figure 2.7 shows a schematic all conditions during the task. The target images were between 5 and 7 cm in projected size and subtended an average visual angle of 3.4 degrees. The attention getter were between 10 and 10.5cm in projected size and subtended an average visual angle of 5.85 degrees. The distance between attention getter and target was 25 cm.

#### 2.2.2.3 Gift Wrap and Delay

The Gift wrap and delay task has been extensively used and targets delay of gratification, a function of effortful control. The procedure follows Kochanska and Kim (2014) and Kochanska et al. (2000). Briefly, during the wrapping phase of the task, children waited –without peeking– while a gift was being noisily wrapped behind him or her (duration: 1 minute). During the delay phase, children waited in the seat –without touching the gift– while the experimenter left the room to get a bow (duration: 3 minutes). I followed the coding procedure of Kochanska and Kim (2014), where higher scores reflect better effortful control.

#### 2.2.2.4 Behavioral Questionnaire

The very short forms of the Early Childhood Behavior Questionnaire (ECBQ; Putnam et al., 2006) and the Children's Behavior Questionnaire (CBQ; Rothbart et al., 2001) were used for parent reports of temperament in toddler and preschool children. Parents of participants aged 24 to 36 months completed the ECBQ, while participants older than 36 months completed the CBQ. These questionnaires assess temperament by measuring individual differences in reactivity and self regulation (Rothbart et al., 2001). In this study, I only used factor scores for effortful control. Factor analysis from the longer version of the CBQ has shown that the effortful control factor loads on components of inhibitory control, attentional focusing, low intensity pleasure and perceptual sensitivity.

#### 2.2.2.5 Minnesota Executive Function Scale (MEFS$^{TM}$)

MEFS$^{TM}$ (Carlson & Zelazo, 2014) is an executive function iPad assessment based on the Dimensional Change Card Sort task (DCCS; Zelazo, 2006). The task requires children to match and sort a variety of cards according to the dimensions of the target cards (e.g., size, color, shape). At each level, they have to follow one rule, and then switch to a new one. To play this game, children need to integrate different components of EF, e.g., they need to pay attention, remember the current rule, and think flexibly. The task difficulty increases as levels increase. The task has been found to be reliable (Beck, Rees, Frith, & Lavie, 2001) and valid (Carlson, Zelazo, & Faja, 2013) in a sample of more than 5,000 children, and has been found to be predictive of school readiness and achievement over and above IQ (Carlson et al., 2013; Hassinger-Das, Jordan, Glutting, Irwin, & Dyson, 2014).

In a given level, children were presented with a sorting card and two equidistant boxes affixed with target cards specified by the current level. At the beginning of the level, children received demonstration trials and rule checks which ensured they understood the rules of the level they would subsequently play (e.g., for level 1A: ”Look, I have this boxes here. This one has a cat on it and this one has a cow on it. This is the cow game. In the cow game, all the cows go in the cow box because that’s where they belong! See here is a cow. It goes in the cow box. (experimenter drag) Can you put this cow where it goes? (child drag)”).

The rule was stated on the first few (2) trials (e.g., ”If it’s a cow, then it goes here.”) and the relevant dimension was subsequently highlighted (e.g., ”Here is a cow.”). On following trials, instead of repeating the rule, a prompt was given to ensure children were ready for subsequent trials (e.g., ”Get ready!”). After 5 trials, the experimenter announced that a new game with a different rule would start (e.g., for level 1B: ”Now we’re going to play a different game. We’re not going to play the cow game anymore. We’re going to play the duck game. In the duck game, the ducks go in the duck box because that’s where they belong! Okay, let’s play!”), and 5 more trials ensued. Age-appropriate starting level was highlighted by the app based on test norms. Testing progressed if a criterion (80%) score was met for each level and continued until the child failed a level. If the criterion score was not met at starting level, the app retrogressed levels until a lower level was passed (and thus setting a basal level). Scoring was automatically calculated by the app based on the *highest level passed* (range of 0–7). Additional scoring measures include a *Total Score* which takes into account accuracy and reaction time, as well as, a *Standard Score* based on age norms. Figure 2.8 shows examples of the levels participants completed in this study.

Look, I have these boxes here. This one has a horse on it, and this one has a duck on it. This is the duck game. In the duck game, all the ducks go in the duck box because that's where they belong! (tap + button)

Look, I have these boxes here. This one has a big elephant on it and this one has a little elephant on it. This is the elephant game. In the elephant game, all the big elephants go in the big elephant box and all the little elephants go in the little elephant box. (tap + button)

Look, I have these boxes here. This one has a frog on it and this one has a butterfly on it. This is the shape game. In the shape game, all the frogs go here and all the butterflies go here. (tap + button)

Look, I have these boxes here. This one is orange and this one is green. This is the color game. In the color game, all the orange ones go here and all the green ones go here. (tap + button)

Figure 2.8: Minnesota Executive Function Task (MEFS$^{TM}$)

## 2.2.3 Analysis Method

### 2.2.3.1 Task by Task analysis

For the eye-tracking tasks, data were pre-processed using Data Viewer (SR-Research, Ontario, Canada). Fixations with a duration less than 100ms were merged with a neighboring fixation, if the latter was within 1°. If neighboring fixations did not meet this criteria or were not temporally contiguous, the short fixation (<100ms) was discarded from analysis.

Trials were segmented into periods of interest (IP) using message-based events. Areas of interest (AOI) were set to be 50% bigger than target objects to account for calibration errors and drifts in the eye tracker. Sample reports were exported and raw gaze position was further analyzed using the statistical package R (R. C. Team, 2017). Age in days was included in all analysis as a continuous variable.

**2.2.3.1.1 VWM-PL** Looking to the change side and non-change side at each point in time during the trial was aggregated into 100ms time bins, allowing calculation of the proportion of looks to the target (change side). To allow for the best possible statistical modelling of these time series data, the data was trimmed to start at 2000ms (at which point participants would have seen 3 full presentations) and end at 8000ms (the last two seconds of data are noisy because fewer participants maintained attention for the full 10s trial duration).

Proportion of looks to the changing side through time were fit with a binomial hierarchical model estimated with a Laplace approximation using the glmmTMB package (Brooks et al., 2017) and eyetrackingR (Dink & Ferguson, 2016) in the statistical package R (R. C. Team, 2017). The model was fit with septic orthogonal polynomials of the time term (Mirman, 2014), that is, the data were modelled with time, time squared, up to time to the power 7, but scaled and centred so as to not be correlated with one another. In addition, the model contained fixed effects of Age in days (scaled and centered) and Load (low, medium, high). Each of the seven time terms were nested as a random effect within participant, along with allowing each participant a random intercept for a maximally-specified model.

Bootstrapped smoothed divergence analysis was then performed to ascertain when during the length of the trial participants looked significantly more to the changing side (>.50) vs the non-changing side. To do this, I used a modified function from the eyetrackingR (Dink & Ferguson, 2016) package. This allowed us to conduct a statistical test that operated over a smoothed version of the data (similar to Wendt, Brand, & Kollmeier, 2014). This method returned a list of divergences between participants' looking and a change preference criteria (set to >.50) based on time windows in which the 95% confidence intervals did not include 0.5 (i.e., p <.05).

**2.2.3.1.2 VWM-4Sq** The analysis followed the same steps as above with some changes to accommodate the difference in the trial structure. Specifically, the trial was partitioned into a memory phase (0-1000ms) and a testing phase (1500-4500ms). I focused on changing trials and loads 2-4, and only looked at the testing phase for analysis purposes.

Proportion of looks to the changing side through time were modelled in the same way as above, with the limitation that the loads in this task have different chance levels due to the number of items presented (e.g., for load 2 chance is 0.50, for load 3 is 0.33, and for load 4 is 0.25). For the smoothed divergence analysis, the change preference by load were base lined at 0 (e.g., proportion - chance, such that chance is now set at 0.0) so I could directly compared the divergence results. This resulted in a list of divergences between participant's looking and a change preference criteria (set to >0.0) based on time windows in which the 95% confidence intervals did not include 0 (i.e., p <.05).

**2.2.3.1.3 IOWA** Balanced Integration Scores (BIS) was calculated for each condition using the R script provided by Liesefeld and Janczyk (2019). BIS combines reaction times and error rates in a way that strongly attenuates speed-accuracy trade-offs using the following equation

$$BIS = z(PC) - z(RT),$$

where $z$ denotes standardised z scores; PC is the percent correct, and RT is reaction time.

BIS scores were fit with a linear mixed model estimated by REML using the lme4 package (Bates, Mächler, Bolker, & Walker, 2015) in R (R. C. Team, 2017). The model was fit with a three-way interaction of age in days, congruency condition (valid, invalid, double, control), and competition condition (competition, no competition), along with allowing each participant a random intercept for a maximally-specified model.

**2.2.3.1.4 UEA** To make sure participants learned the contingency between the AG and the subsequent target location, looking to the target item at each point in time during the trial was aggregated into 100ms time bins, from which I calculated the proportion of looks to the target.

For anticipatory looking trials, if the child oriented to the target item during the anticipatory period (100ms into the gap period until 100ms after the onset of the target), it was coded as an anticipation (1). If they oriented only after the stimulus was presented, it was coded as non-anticipation (0). Incorrect anticipations were coded as invalid (-1). Reaction times for correct anticipatory looks were calculated. Proportion of anticipatory looks were fit with a binomial hierarchical model estimated with Laplace approximation using the glmmTMB package (Brooks et al., 2017) and eyetrackingR (Dink & Ferguson, 2016) in the statistical package R (R. C. Team, 2017). The model was fit with fixed effects of Age in days (scaled and centered), Phase (training, test) and Gap Duration (450ms, 900ms), along with allowing each participant and trial a random intercept for a maximally-specified model.

For disengagement trials, BIS scores were calculated in the same way as above and captured participant's efficiency of disengagement after target onset. BIS scores were fit with a linear model using the lme4 package (Bates et al., 2015) in R (R. C. Team, 2017). The model was fit with age in days as a predictor.

**2.2.3.1.5 Gift wrap and delay** I followed the coding procedure of Kochanska and Kim (2014), where higher scores reflect better effortful control. Coding took place as follows: during the wrapping phase, children's behavior was coded from 1 (turns fully around to look) to 5 (does not peek). During the delay phase, touching behavior was coded from 1 (opens gift) to 4 (never touches), and seating behavior from 1 (in seat for less than 30 sec) to 4 (in seat for more than 2 min). Peeking behavior was also coded for this phase following the same procedure as the wrapping phase. Additionally, latencies to peek, turn body around, touch the gift, and to leave seat were also coded. All coding was done using DataVyu Coding Software (D. Team, 2014).

Peeking behavior was modelled with a proportional odds logistic regression model using the porl function in the MASS package (Venables & Ripley,

2002) in the statistical package R (R. C. Team, 2017). The model was fit with age, gender, and task phase (wrap and delay) as predictors. The model was then simplified using log likelihood tests.

**2.2.3.1.6 Behavioral Questionnaire** The Effortful Control factor scores were computed. These scores were were fit with a linear model using the lme4 package (Bates et al., 2015) in R (R. C. Team, 2017). The maximally specified model was fit with age in days and gender as a predictor. The model was then simplified using log likelihood tests.

**2.2.3.1.7 MEFS** MEFS Highest Level Passed was fit with a linear model using the lme4 package (Bates et al., 2015) in R (R. C. Team, 2017). The maximally specified model was fit with age in days and gender as a predictor. The model was then simplified using log likelihood tests.

## 2.3 Results

### 2.3.1 VWM-PL

Looking proportions were modelled with a hierarchical binomial model to examine the effects of change preference, Load, and Age (in days) over time in the task. The model utilized orthogonal septic polynomials of the time term to capture the model fit (Mirman, 2014). Fixed effects were tested with a Wald chi-squared test to assess the contribution of each parameter in reducing residual deviance of the model. The results indicate evidence for an interaction effect between the linear, square, and cubic time terms and Age, an effect of all seven time terms and Load, as well as all 3-way interactions (see Table A.1). Thus, there is some evidence that the time course of looking to the change side varies by age, strong evidence that time course of looking to the change side varies by Load, and evidence that the amount by which the time course of looking to the change side varies at each Load differs across age. The model fit to the raw data can be seen in Figure 2.9.

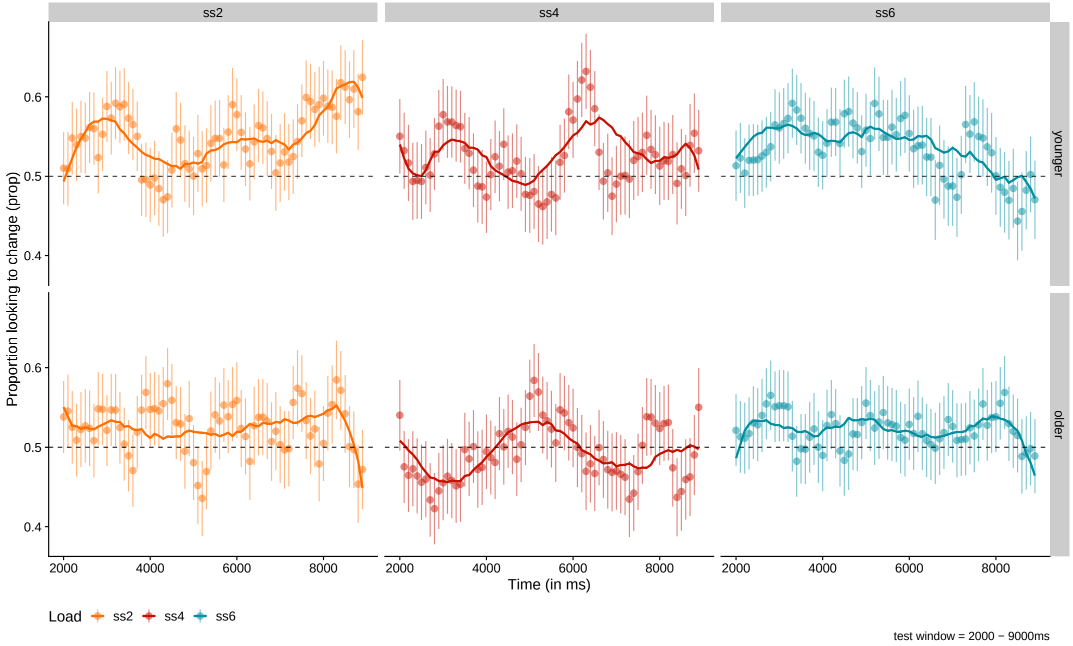

Figure 2.9: Model predicted proportion looking to change side by load by age. Grey dotted line depicts chance performance (0.50). Age in days was median split to facilitate visualization. Points show the raw data. Line shows the model predictions.

Proportion looking to the change side showed considerable fluctuations through time across loads and age. Contrasting performance across age, in the low load, it is evident that younger participants showed above chance performance at the beginning and towards the end of the trial while older children showed above chance performance for a brief period towards the end of the trial, before dropping to look at the no-change side. For the medium load, older kids showed above chance performance in the middle of the trial, while younger children showed above chance performance at the beginning and middle of the trial. On the high load, the young kids show some preference for the changing side across the majority of the trial while older children only show small epochs at the beginning and end of the trial where it seems they preferred to look at the changing side.

Results from the divergence analysis show that participants' looking dynamics diverged from chance in small bursts of time at the beginning, middle and towards the end of the trial (see Figure 2.10). But there is considerable variability across time.

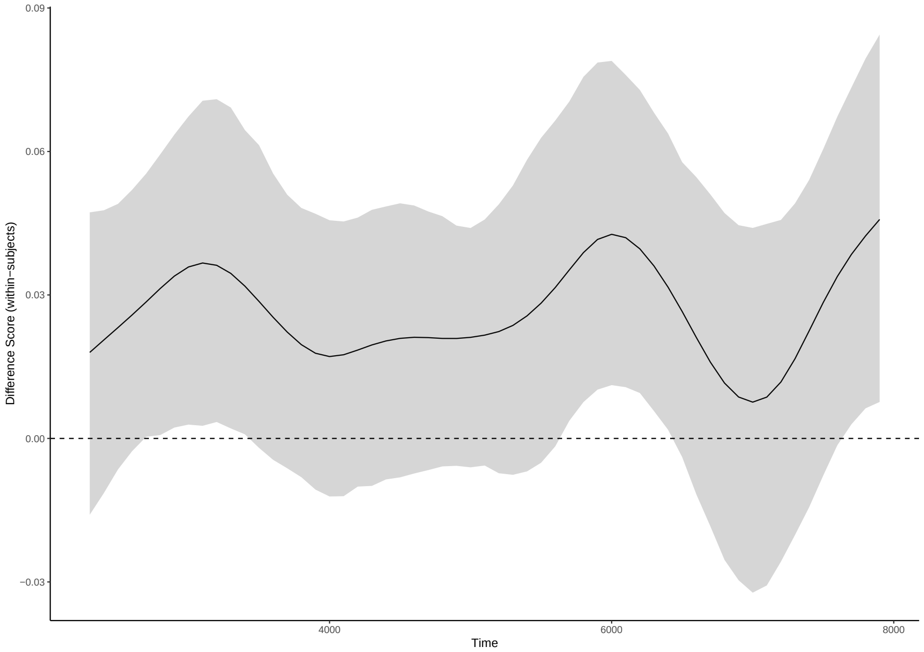

Figure 2.10: Divergence plot showing period of the trial where participant's looking is significantly different from chance (chance = .50).

To create a VWM-PL score that I could move forward for further analysis, I averaged looking across the early (2.7 - 3.5 s) and middle (5.6 - 6.5 s) epochs identified in the divergence analysis. Change preference score across loads were not significantly different from each other. For younger kids, looking in the high load was significantly greater than chance ($p < 0.02$) but this was not the case on any of the other comparisons (see Figure 2.11). Table A.2 shows the comparisons against chance at each load.

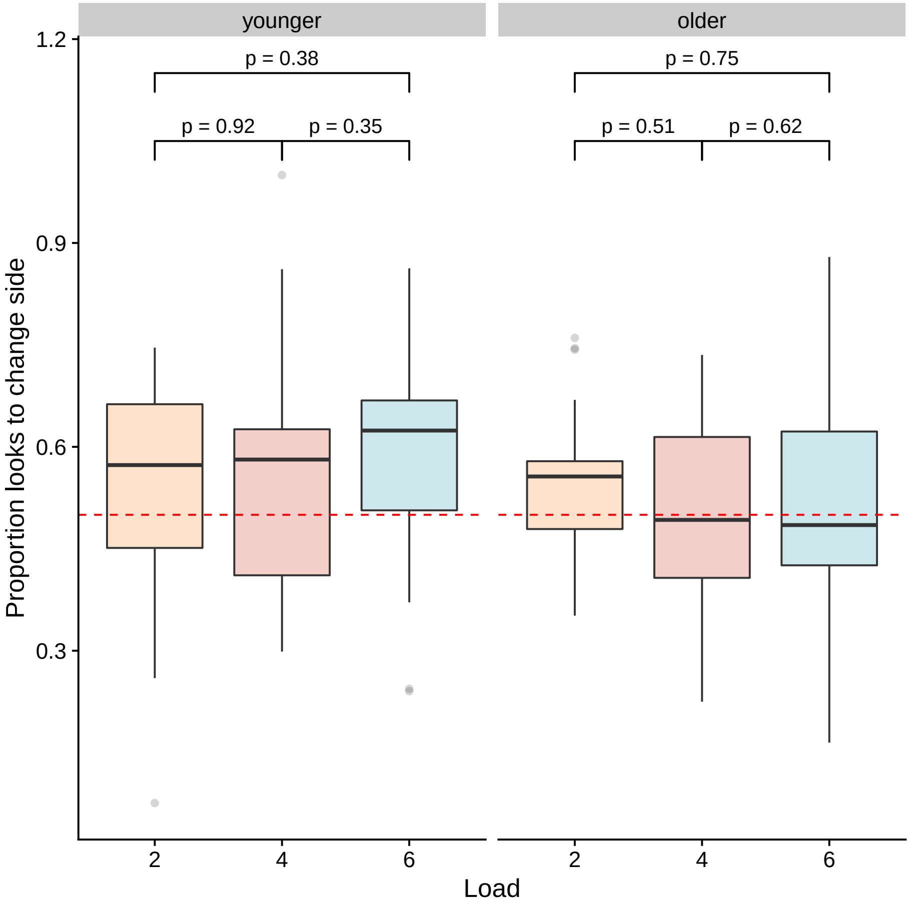

Figure 2.11: VWM-PL change preference score averaged across the two relevant windows identified in the divergence analysis. Red dotted line depicts chance performance (0.50). Age in days was median split to facilitate visualization.

### 2.3.2 VWM-4Sq

Looking proportions were modelled with a hierarchical binomial model to examine the effects of change preference, Load, and Age (in days) over time. The model utilized orthogonal septic polynomials of the time term to capture the model fit (Mirman, 2014). Fixed effects were tested with a Wald chi-squared test to assess the contribution of each parameter in reducing residual deviance of the model. The results indicate evidence for an effect of age, an interaction effect between the square and septic time terms and Age, an effect of all seven time terms and Load, as well as all 3-way interactions (see Table A.3). Thus, there is some evidence that the time course of looking varies by age, strong evidence that time course of looking to the change item varies by Load, and evidence that the amount by which the time course of looking to the change item varies at each Load differs across age. However, the load effects need to be taken with a grain of salt due to the different chance levels. The model fit to the raw data can be seen in Figure 2.12.

Similar to the VWM-PL results, proportion looking to the change item showed considerable fluctuations through time across age and loads. All participants showed a clear preference to look at the changed item in the low load, with the older kids showing a slightly higher preference that young children. However there is a clear developmental pattern in the medium and high loads such that older kids showed a preference to look at the changed item faster than younger kids.

The results from the divergence analysis show that participants' looking dynamics diverged from chance from 1.5 to 3.5 in the test phase of the trial (see Figure 2.13.

To create a VWM-4Sq score that I could move forward for further analysis, I averaged looking across the window identified in the divergence analysis. Change preference score across loads were not significantly different from each other. For younger kids, looking to the changed item in the low load was significantly greater than chance ($p < 0.001$). For the older kids, looking to the changed item in all loads was significantly greater than chance (ss2: $p < 0.001$, ss3: $p < 0.01$, ss4: $p < 0.05$; see Figure 2.14). Table A.2 shows the comparisons against chance at each load.

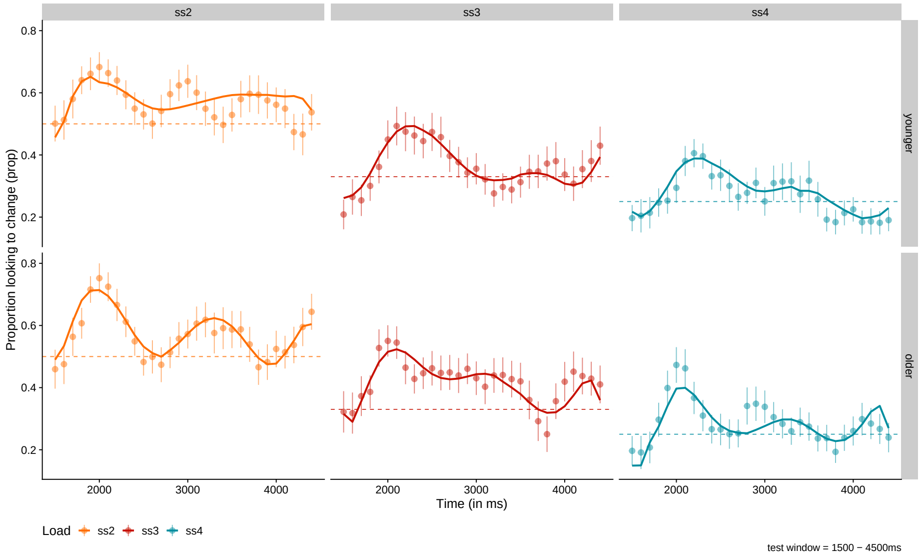

Figure 2.12: Model predicted proportion looking to changed item by load by age. Color coded lines show load-specific chance level (ss2 = 0.50, ss3 = 0.33, ss4 = 0.25). Age in days was median-split to facilitate visualization.

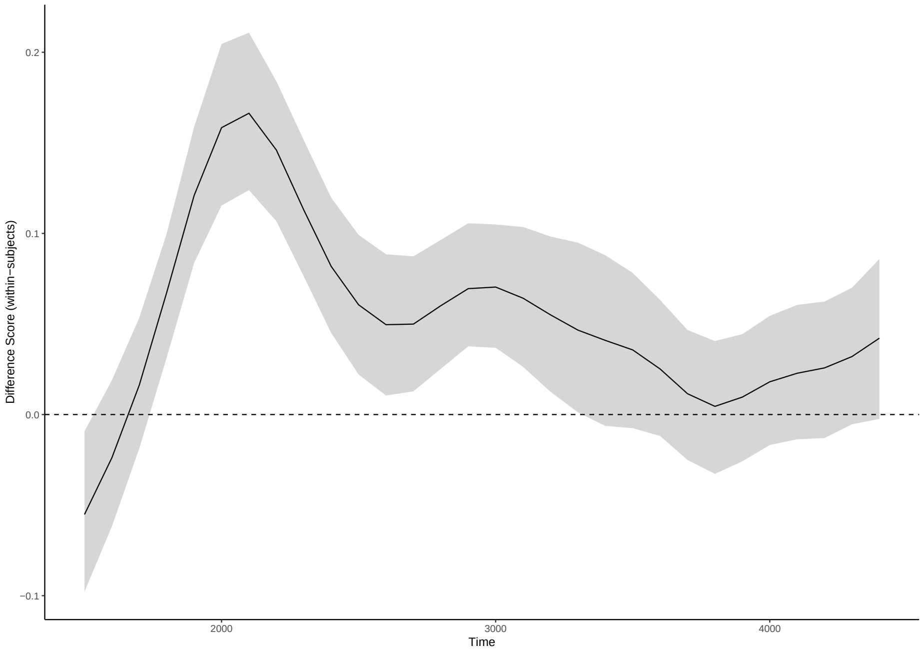

Figure 2.13: Divergence plot showing period of the trial where participant’s looking is significantly different from chance (chance = 0).

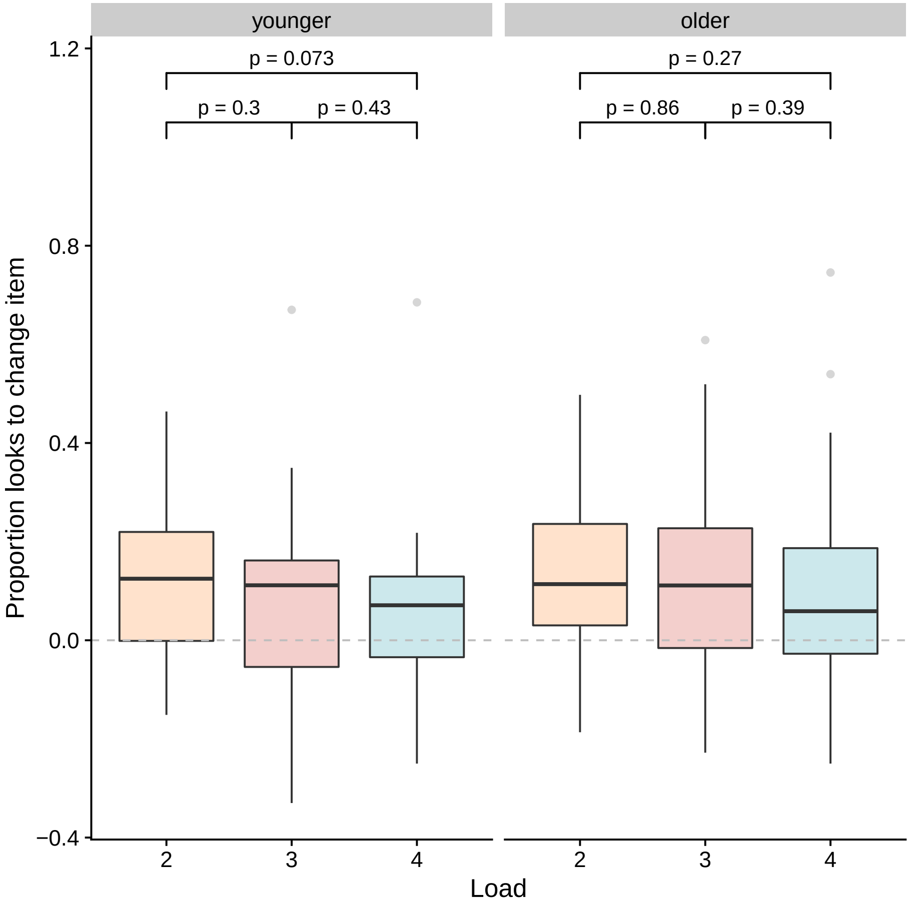

Figure 2.14: VWM-4Sq change preference score in the relevant window identified in the divergence analysis. Grey dotted line depicts chance performance (0.0). Age in days was median split to facilitate visualization. Points show the raw data. Line shows the model predictions.

#### 2.3.2.1 Contrasting performance across VWM tasks

As mentioned above, in the present study, I used two VWM preferential looking tasks. Contrasting performance across tasks, in figure 2.15, we can see that there are differences in looking dynamics across both tasks. As the figure shows, there are clear developmental trajectories in the VWM-4Sq task. While looking dynamics in the VWM-PL show many individual differences across time and loads, there are clear periods during the trial that show systematic looking patterns where looking is above and below chance. One such period is from 2.3-4 seconds, by which time participants would have seen 3 full presentations of the displays. Note that this is close to the time window used in VWM-4Sq (1.5-3.5 s). Looking differences across tasks could be explained by a variety of factors given the procedural differences. For instance, the VWM-4Sq is a one-shot task, that is, participants only see one presentation of the changed item and thus it does not rely on long-term memory traces.

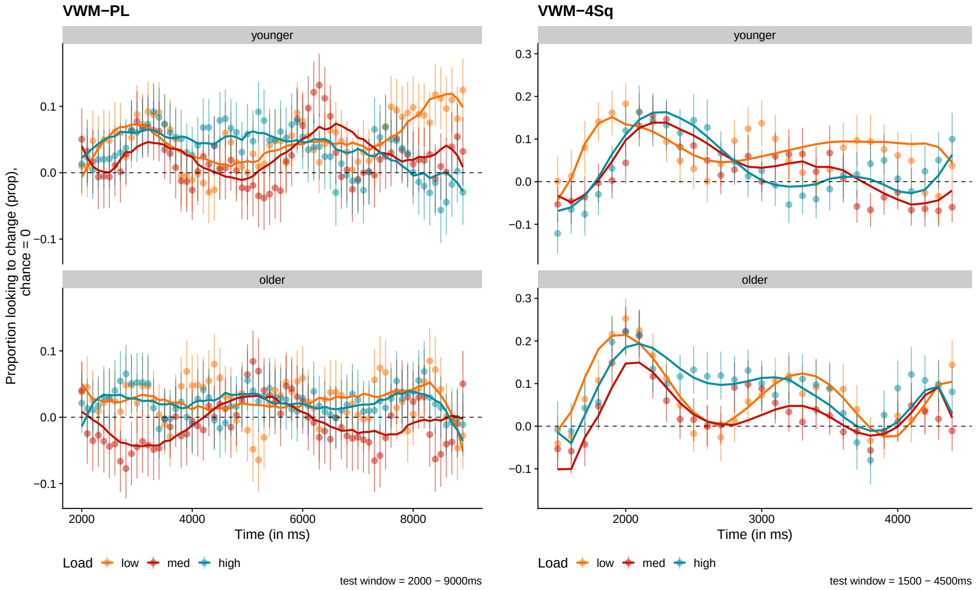

Figure 2.15: Model predicted proportion looking to changed item by load by age. Age in days was median split to facilitate visualization, with younger kids shown at the top, and older kids in the bottom. Left panel shows VWM-PL results, right panel shows VWM-4Sq. Grey dotted line depicts chance performance (0.0).

### 2.3.3 IOWA

BIS scores were modelled with a linear mixed model to examine the effects of age (in days), congruency, and competition. Fixed effects were tested with a Wald chi-squared test to assess the contribution of each parameter in reducing residual deviance of the model. The results indicate evidence for an effect of age, congruency, and competition, as well as an interaction between congruency and competition (see Table A.4). Thus, there is some evidence that the BIS score varies by age, strong evidence that BIS score varies by congruency condition as well as competition condition, and strong evidence that the amount by which BIS score by congruency condition differs across competition condition. The model fit to the raw data can be seen in Figure 2.16.

Thus, as expected, participants' scores increased as they grew older ($p$ = 0.013). Similarly, performance was better in the no competition condition vs the competition condition ($p$<0.001). Replicating Ross-Sheehy et al. (2015), an invalid cue resulted in worse performance when compared to a valid cue ($p$ <0.001). This also varied by age, with participants showing similarly impaired performance across ages in the invalid condition compared to the increase in performance over age shown in the presence of a valid cue ($p$ = 0.002). Performance was worse when there was no cue (control condition) preceding the target when compared to the presence of a valid cue ($p$ <0.001). This effect also varied by age, with older children showing better performance than younger children ($p$ = 0.044).

### 2.3.4 UEA

#### 2.3.4.1 Contingency Learning

Figure 2.17 shows the proportion looking to the target item through time on test trials (200ms after target onset). Recall that on 'test' trials there are two items on the screen thus, a preference to look to the target item gives us an index that they learned the contingency between attention getter and target location. The figure shows that all participants learned the contingency, irrespective of age.

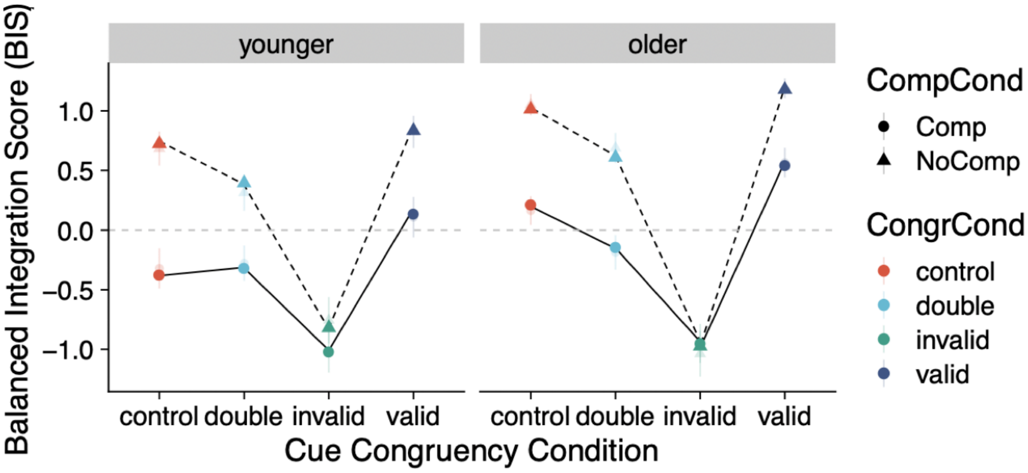

Figure 2.16: Model predicted BIS by condition by age. Age in days was median split to facilitate visualization. Light points show the raw data. While dark points shows the model predictions. Triangles connected by the dotted line show the No Comp condition. Circles connected by the solid line show the Comp condition. Zero is the mean score across conditions.

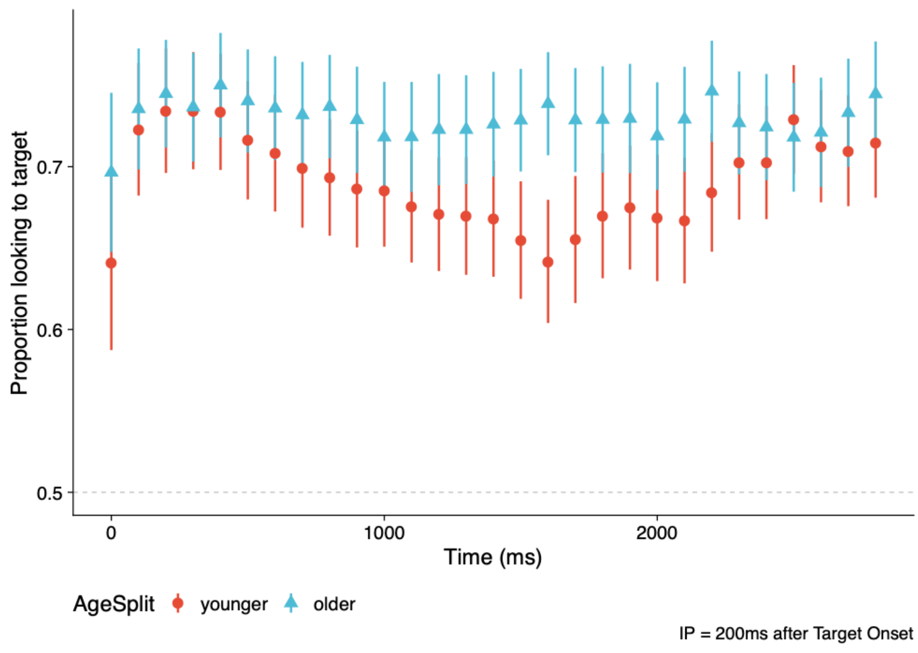

Figure 2.17: Proportion looking to target item on test trials by age. Age in days was median split to facilitate visualization. Dotted line depicts chance (0.50).

#### 2.3.4.2 Anticipatory Looking

Anticipatory Looking proportions were modelled with a hierarchical binomial model to examine the effects of phase (train, test), gap duration (450, 900) and Age (in days) over time. Fixed effects were tested with a Wald chi-squared test to assess the contribution of each parameter in reducing residual deviance of the model. The results indicate evidence for an effect of age (see Table 2.2). Thus, there is some evidence that the proportion of anticipatory looking vary by age, such that older participants were more likely to produce anticipatory looks. The model fit to the raw data can be seen in Figure 2.18.

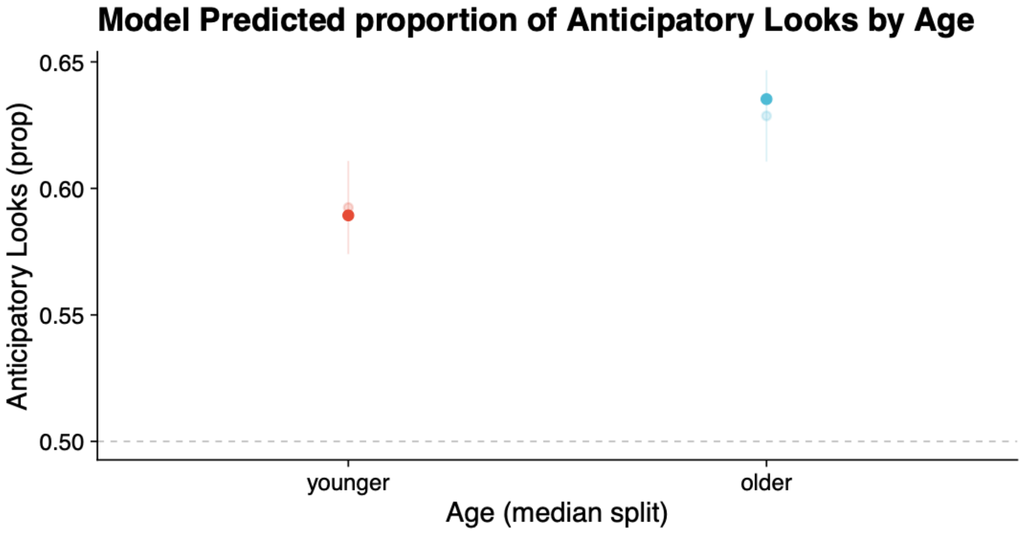

Figure 2.18: Model predicted proportion of Anticipatory Looks by age. Age in days was median split to facilitate visualization. Light points show the raw data. Dark points shows the model predictions. Dotted line depicts chance (0.50).

#### 2.3.4.3 Disengagement

BIS scores were modelled with a linear model to examine the effect of age (in days). There is some evidence for an effect of age (see Table 2.3) with older participants showing better performance in the disengagement condition. In

| | Anticipatory Looks | | |
|---|---|---|---|
| *Predictors* | *Odds Ratios* | *CI* | *p* |
| (Intercept) | 1.5 | 1.18 – 1.92 | **0.001** |
| Age | 1.15 | 1.00 – 1.33 | **0.046** |
| Phase | 0.76 | 0.56 – 1.04 | 0.087 |
| Gap Duration | 1.26 | 0.91 – 1.74 | 0.158 |
| **Random Effects** | | | |
| $\sigma 2$ | 3.29 | | |
| $\tau 00_{ID}$ | 0.21 | | |
| $\tau 00_{Trial}$ | 0.03 | | |
| ICC | 0.07 | | |
| $N_{ID}$ | 110 | | |
| $N_{Trial}$ | 34 | | |
| Observations | 1433 | | |
| Marginal $R^2$ / Conditional $R^2$ | 0.010 / 0.077 | | |

Table 2.2: Regression results using Anticipatory Looking as the criterion

particular, they disengaged from the central AG more accurately and faster than younger participants (see Figure 2.19).

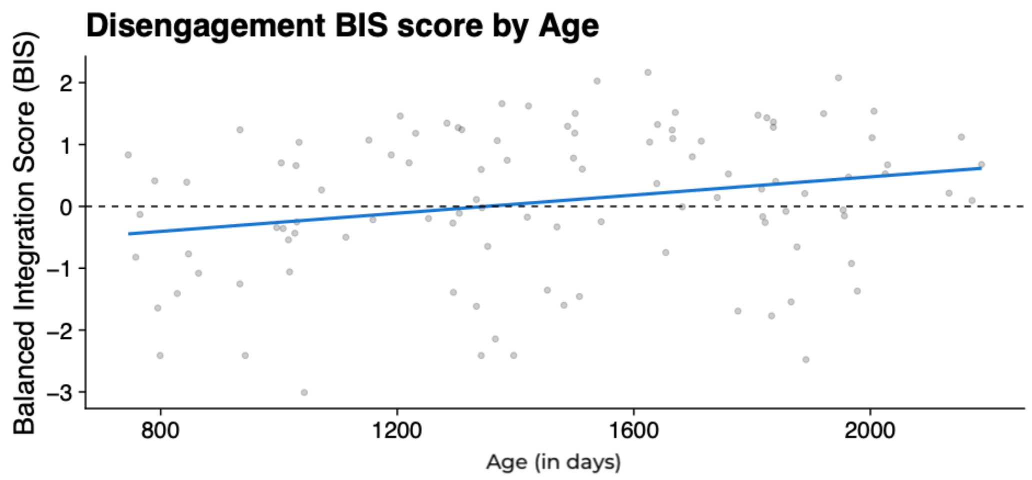

Figure 2.19: Disengagement BIS score by age. Line shows model predicted bis scores.

Table 2.3: Regression results using disengagement BIS scores as the criterion

| *Predictor* | *b* | *b* 95% CI [LL, UL] | *sr*$^2$ | *sr*$^2$ 95% CI [LL, UL] | *r* | *Fit* |
|---|---|---|---|---|---|---|
| (Intercept) | 0.08 | [-0.14, 0.31] | | | | |
| Age | 0.29* | [0.06, 0.51] | 0.06 | [.00, .16] | .24* | |
| | | | | | | R$^2$ = .059*<br>95% CI[.00,.16] |

*Note. A significant b-weight indicates the beta-weight and semi-partial correlation are also significant. b represents unstandardized regression weights. beta indicates the standardized regression weights. sr*$^2$ *represents the semi-partial correlation squared. r represents the zero-order correlation. LL and UL indicate the lower and upper limits of a confidence interval, respectively.*
** indicates p <.05. ** indicates p <.01.*

### 2.3.5 Gift Wrap and Delay

Peeking behavior was modelled with a proportional odds logistic regression model to asses the effect of age (in days) and task phase (wrap and delay) using the porl function in the MASS package (Venables & Ripley, 2002) in the statistical package R (R. C. Team, 2017).

There is strong evidence that older children were more likely to not peek during the wrapping phase of the task while younger kids were more likely to turn around but turn back forward. In the delay phase, children were more likely to turn around but turn back forward. The raw data can be seen in figure 2.20 and the model predicted probabilities of peeking behavior in the task can be seen on figure 2.21.

### 2.3.6 Temperamental Effortful Control

Effortful control factor scores were modelled with a linear model to examine the effect of gender. The results indicate there is a gender effect (see Table 2.5) such that girls have higher effortful control scores than boys (see Figure

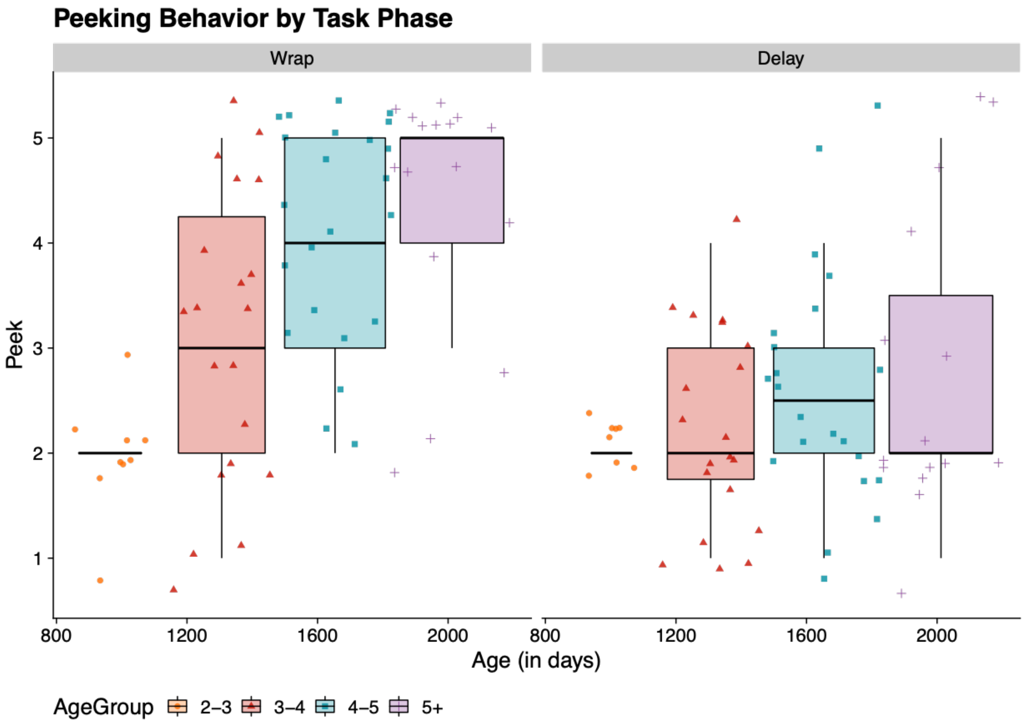

Figure 2.20: Peeking behavior by task phase. Age in days was grouped into age groups to facilitate visualization.

| | | **peek** | |
|---|---|---|---|
| *Predictors* | *Odds Ratios* | *CI* | *p* |
| Age | 2.29 | 1.62 – 3.24 | **<0.001** |
| task | 2.48 | 1.75 – 3.52 | **<0.001** |
| Age x task | 1.56 | 1.12 – 2.17 | **0.009** |
| (Intercept: 1—2) | 0.06 | 0.03 – 0.12 | **<0.001** |
| (Intercept: 2—3) | 0.64 | 0.43 – 0.95 | **0.027** |
| (Intercept: 3—4) | 2.15 | 1.41 – 3.26 | **<0.001** |
| (Intercept: 4—5) | 4.55 | 2.81 – 7.36 | **<0.001** |
| Observations | 133 | | |
| $R^2$ Nagelkerke | 0.353 | | |

Table 2.4: GW results

2.22).

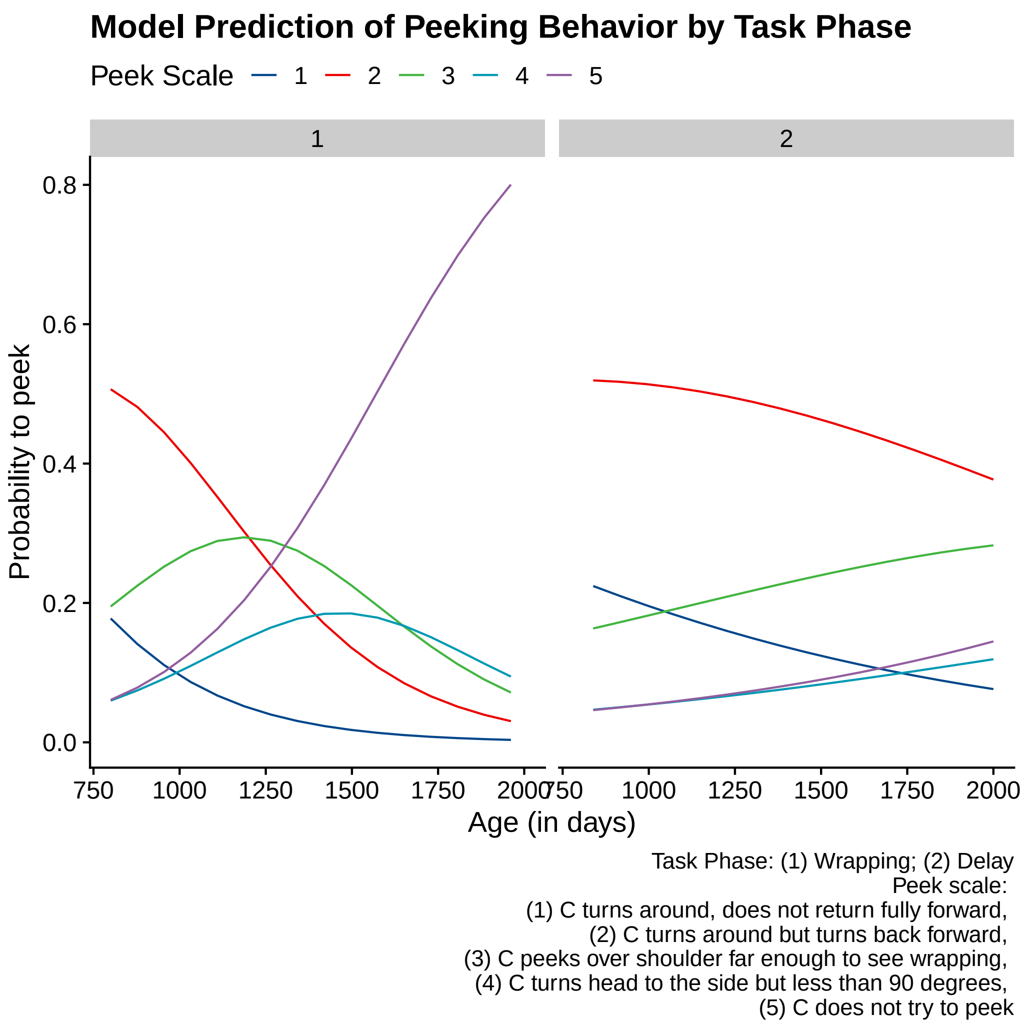

Figure 2.21: Model Prediction of Peeking Behavior by Task Phase.

### 2.3.7 MEFS

MEFS highest level passed was modelled with a linear model to examine the effect of age (in days) and gender. The results indicate there is evidence for an effect of age (see Table 2.6) such that older participants have higher level passed than younger participants (see Figure 2.23).

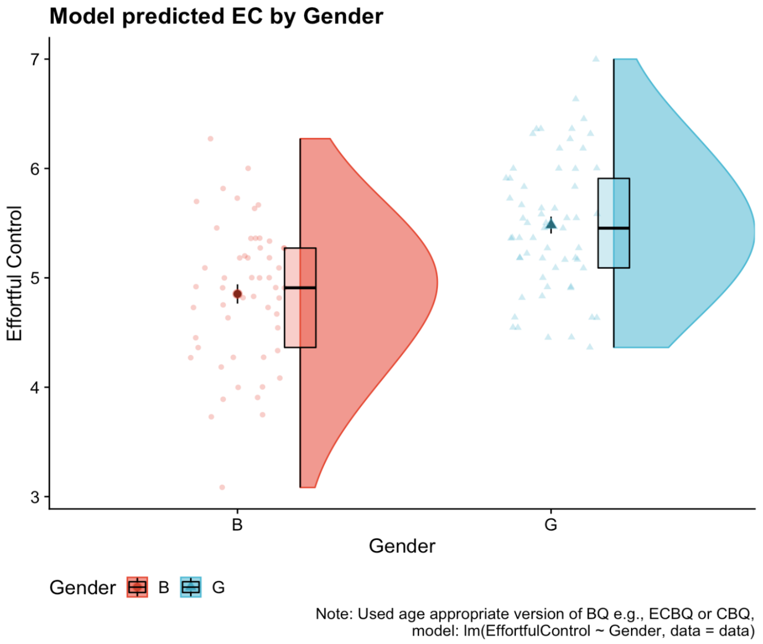

Figure 2.22: Effortful Control by Gender. Dark points show the model predicted data. Light points show the raw data. While dark points shows the model predictions.

Table 2.5: Regression results using Effortful Control as the criterion

| Predictor | *b* | *b* 95% CI [LL, UL] | $sr^2$ | $sr^2$ 95% CI [LL, UL] | Fit |
|---|---|---|---|---|---|
| (Intercept) | 4.85** | [4.68, 5.02] | | | |
| Gender | 0.63** | [0.40, 0.86] | 0.21 | [.09, .33] | |
| | | | | | $R^2$ = .205**<br>95% CI[.09,.33] |

*Note*. A significant *b*-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. $sr^2$ represents the semi-partial correlation squared. LL and UL indicate the lower and upper limits of a confidence interval, respectively.
* indicates p <.05. ** indicates p <.01.

### 2.3.8 Path Analysis

Uncorrected correlations between study measures are shown in Figure 2.24. Figure 2.25 shows scatter plots for these correlations. Results show that age was correlated with both hot and cold executive functions measures (namely

Table 2.6: Regression results using MEFS Highest Level Passed as the criterion

| *Predictor* | *b* | *b*<br>95% CI<br>[LL, UL] | *$sr^2$* | *$sr^2$*<br>95% CI<br>[LL, UL] | *Fit* |
|---|---|---|---|---|---|
| (Intercept) | 3.21** | [2.95, 3.48] | | | |
| Age | 1.50** | [1.24, 1.77] | 0.39 | [.26, .51] | |
| Gender | -0.30 | [-0.66, 0.07] | 0.01 | [-.01, .03] | |
| Age x Gender | -0.24 | [-0.61, 0.13] | 0.01 | [-.01, .02] | |
| | | | | | $R^2$ = .656**<br>95% CI[.55,.72] |

*Note. A significant b-weight indicates the semi-partial correlation is also significant. b represents unstandardized regression weights. sr2 represents the semi-partial correlation squared. LL and UL indicate the lower and upper limits of a confidence interval, respectively.*
** indicates p <.05. ** indicates p <.01.*

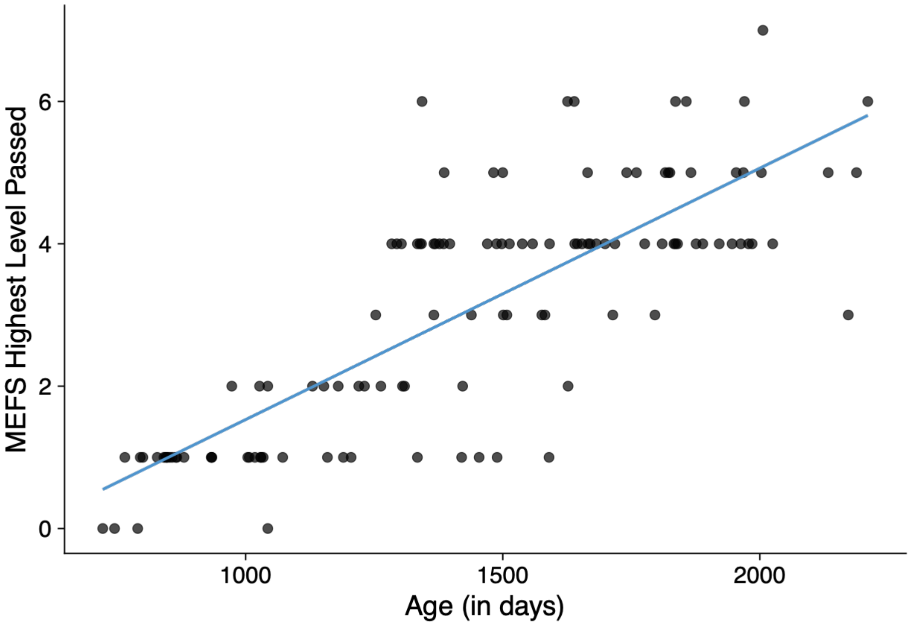

Figure 2.23: MEFS highest level passed by age.

Gift Wrap peek score (r(103) = 0.56, p <.001) and MEFS Highest Level Passed (r(103) = 0.80, p <.001)), such that older kids performed better on both executive functions measures. Notably, MEFS and Gift Wrap were also positively correlated (r(103) = 0.60, p <.001). However, measures of hot executive functions (effortful control and gift wrap peek score) were not correlated (r(103) =

Figure 2.24: Correlation matrix shows the correlations (uncorrected) across all variables. Blue depicts positive correlations and red depicts negative correlations. The 'x' denotes correlations that were not significant. The size and intensity of the color of the circle denotes the strength of the relationship.

0.14, p >.1). Note there is missing data in gift wrap, thus rather than creating a composite score across correlated variables, I chose to keep all individual measures of executive functions in further analyses. Cool executive function (MEFS highest level passed) was negatively related to working memory performance in the high load (r(103) = -0.21, p <.05), such that participants with better EF showed worse performance on the more complex working memory load. Anticipatory looking and Effortful control were positively correlated (r(103) = 0.23, p <.05), such that participants with a higher effortful control score were more likely to produce anticipatory looks. Anticipatory looking

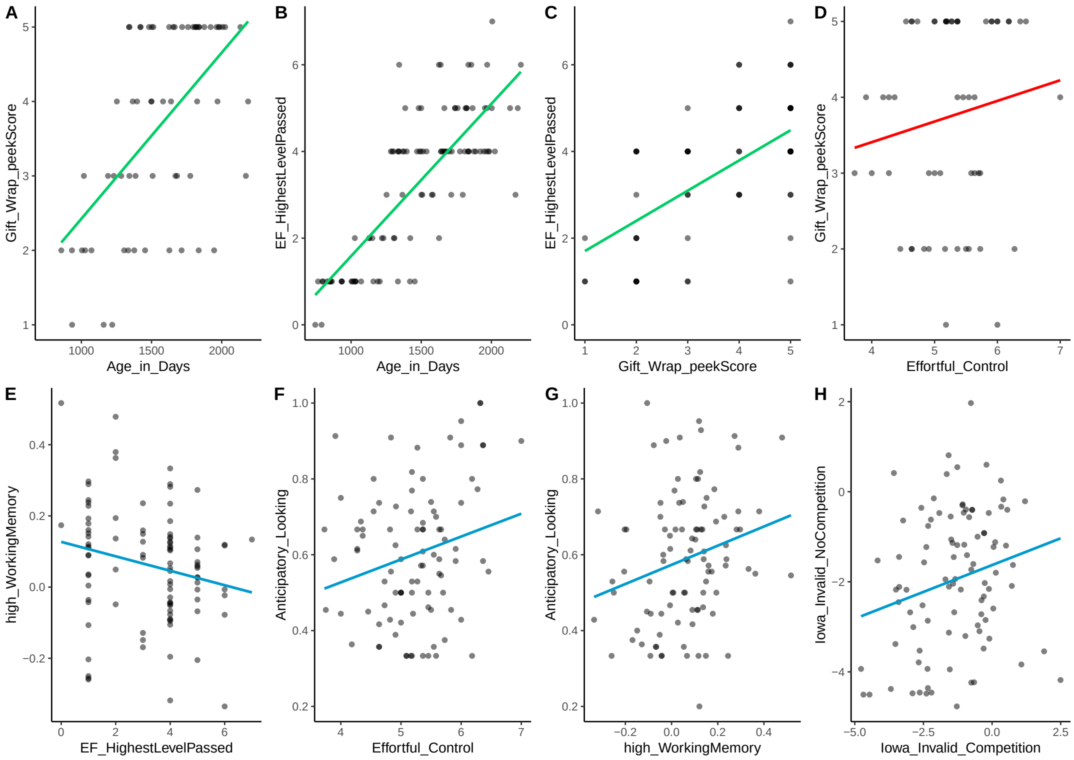

Figure 2.25: Scatter plots of correlations. Green regression line depicts correlations that remained significant after correcting for multiple comparisons. Blue line depicts significant correlations that did not survive correcting for multiple comparisons. Red line depicts correlations that were not significant.

was also positively related to better working memory performance in the high load, (r(103) = 0.24, p <.05). Performance in the invalid competition condition and the invalid no competition condition in the IOWA task were significantly correlated, (r(103) = 0.22, p <.05). Importantly, attention measures across tasks were not correlated. However, after correcting for multiple comparisons, only the correlations between age and both hot and cold executive functions measures (Gift Wrap peek score and MEFS Highest Level Passed), and the correlation between MEFS and Gift Wrap were supported.

A path analysis was run using the lavaan package (Rosseel, 2012) in the statistical package R (R. C. Team, 2017) to simultaneously model relationships between all tasks and how they relate to hot and cold EF. The theoretical model is shown in figure 2.1. Full Information Maximum Likelihood (FIML) estimation was used in the analysis to account for missing data. To evaluate model fit I used several criteria. First, I used the overall chi-square for the model which is a global fit index. For this measure, a nonsignificant p-value indicates a good fit (Kline, 2011). In this model, $\chi^2$ was non-significant, $p$ = 0.300. Three additional measures were used: the root mean square error of approximation (RMSEA), comparative fit index (CFI), and standardized root mean square residual (SRMR). For the CFI, values greater than .95 indicate a good model fit (Hu & Bentler, 1999). The CFI in the model was .993. For RMSEA, which indicates how well the model fit the population covariance matrix, values less than or equal to .05 suggest a good model fit (Hu & Bentler, 1999). The RMSEA in the model was 0.045. Finally, a SRMR less than .08 indicates a good fit. The SRMR in the model was 0.055. In sum, goodness-of-fit indices showed an acceptable model fit ($\chi^2$(5, n = 105) = 6.061, $p$ = 0.300, RMSEA = 0.045 [CI = 0.00, 0.149], CFI = .993, SRMR = 0.055).

Results showed that a higher probability to produce anticipatory looks was related to better 'hot' EF, specifically better effortful control ($\beta$ = .166, SE = .079, $p$ = .035). Further, a higher probability to produce anticipatory looks was positively correlated to better working memory performance in the high load ($p$ = 0.032). Table A.5 shows the standardized coefficients. In sum, going back to figure 2.1, results showed links between executive attention and WM, and executive attention and effortful control. These results indicate that these subcomponents are related but suggests a simpler model is sufficient to explain EC in this period of development.

## 2.4 Discussion

The goal of this study was to explore the development of EF subcomponents in a large age-range developmental cohort with an eye toward exploring whether looking measures of working memory and attention predict ’hot’ and ’cold’ EF. I measured attentional control, visual working memory, effortful control and executive function in children aged 24 to 72 months. Overall, I found age-related changes across all domains, with expected increases in cognitive skill and complexity as children increased in age.

The working memory results showed an effect of age and load such that participants’ behavior was modulated by the number of items shown and their age. Importantly, results show differences in looking dynamics across both VWM tasks and loads. The developmental patterns across age and loads were clearer in the VWM-4Sq task when compared to the VWM-PL, however, we must consider the procedural differences across tasks when comparing performance across them. VWM-PL presents a much longer trial (10s vs 5s), which could present challenges to retain children’s engagement in the task. This could explain the individual variability seen in the results. That said, I should note that I only looked at overall looking dynamics with an eye toward having an index of working memory capacity. There are other indices of performance such as switch rate, mean looking time, and changes in pupil size that could serve as important predictors of WM development in these tasks as reported by Ross-Sheehy and Eschman (2019). It would be useful for future work to examine whether controlling for differences in these looking measures might yield more comparable data across the two tasks.

Results from the IOWA task provided a robust replication of previous work by Ross-Sheehy et al. (2015). We saw widely-reported effects of age, in addition to effects of both invalid cues and competing objects. Critically, work from Ross-Sheehy et al. (2015) was with infants aged 7-10 months. Thus, it is remarkable that I replicated the cue interference and the competition effect in older children with such a simple measure. Importantly, results from this task are systematic, but not related to any of the other measures in this study. Results from this task suggest that individual differences in orienting attention are not related to WM, EF and EC, at least not in this age range. It could be that by this age, the executive attention system dominates children's performance with more direct effects on executive control. This is consistent with Posner et al. (2014) hypothesis that early on (e.g., under the age of 3) executive control is exerted by the orienting attention network but this changes over development, as the executive attention network develops.

The UEA task used in the present study is in its most basic sense a gap overlap task (Elsabbagh et al., 2013) with a contingency learning component to assess anticipatory saccades as a function of learning. The gap-and-overlap task is a well-established measure of occulomotor function used in previous studies to assess attention disengagement skills in infants, children, and adults (e.g., Elsabbagh et al., 2013; Özyurt & Greenlee, 2011; Wass, Porayska-Pomsta, & Johnson, 2011). Results showed incremental development in anticipatory looking and disengagement. While we saw increasing efficiency in disengagement over development, the correlation with age was not significant. In the present study, participants anticipated over 60% of the time which suggests they are quite efficient at this during this developmental period. Importantly, this is consistent with previous examinations of anticipatory looking in visual sequence tasks from 24- to 36-months (Rothbart et al., 2004) and higher than what has been reported with typically developing infants (e.g., 22-27%, see Holmboe et al., 2018; Canfield, Wilken, Schmerl, & Smith, 1995; Haith, Hazan, & Goodman, 1988). Importantly, performance in both attention tasks was not correlated which is consistent with the literature and suggests that the tasks used here are measuring functionally distinct attention systems.

Moreover, two measures of executive control and executive function, Gift Wrap and MEFS, showed a strong age effect such that older participant exhibited better performance and thus had higher executive control scores. When looking at parent-reported effortful control, we did not see a relationship with age but there was a gender difference such that girls had a higher effortful control score than boys. Importantly, MEFS and GW were highly correlated despite missing GW data, but GW and parent-reported effortful control were not related. As can be seen in figure 2.2, there was a considerable number of children who did not provide useable data for the GW task. This was more prevalent in the younger children and there are a variety of reasons for that: (1) task priorities: this task was the last one of the session and, thus, some children became tired or fussy before getting to this part of the session, (2) a considerable number of the younger kids did not want to be in the room without their caregiver and became fussy at the beginning of the task, finally, (3) there were some technical / experimenter errors which resulted in unuseable data.

When looking at relationships between WM and attentional subcomponents and executive control, we saw that anticipatory looking was correlated with both parent-reported effortful control and working memory performance in the high, more complex, load. This is not consistent with previous work with 24- to 36-month olds (Rothbart et al., 2004). They reported that percent anticipation was not related to EC at 24-36mo. Further, as in Geeraerts et al. (2019) and Wass and Smith (2014), I did not find a relationship between disengagement and executive control.

Results from the path analysis showed that the probability to produce an anticipatory look was predictive of participant's effortful control. Furthermore, proportion looking to change in the high WM load was correlated to anticipatory looking such that participants with a higher change preference score, were more likely to produce anticipatory looks. It is important to note that performance across working memory loads was not correlated. These results supports a link between attention and complex WM abilities. A plausible interpretation for these results is that when children are confronted with high WM demands, attention supports behavioral performance.

In contrast, performance in the WM task high load was negatively related with MEFS highest level passed such that children with a higher executive function score, tended to look back and forth between displays (or objects) thus not forming a change preference. In future work, it would be interesting to explore how visual exploratory measures are related to EF, as measured by MEFS. It is important to note that I had two measures of WM. Performance across these tasks was different, making between-subjects comparisons complex given aforementioned procedural differences between tasks. Nevertheless, based on the results reported here, we know that, as a group, these tasks did provide important indices of individuals' cognitive profiles.

One remarkable aspect of this study is that I was able to capture meaningful individual differences across this large developmental period using visual dynamics as dependent measures. These results extend what we know about visual dynamics and their relationship to emerging cognitive abilities into early childhood, highlighting that looking measures can provide meaningful indices of cognitive function beyond infancy. Furthermore, these results provide exciting opportunities to use attentional control as an index of EF development which was also related to WM development. Note that the lack of relationships between these looking-based measures and the executive function outcome measure used in the present study, MEFS, could be due to the heavy language component of this measure. In contrast to the eye tracking tasks, this procedure relies on children's understanding of verbal instructions from an experimenter. In the present study, I did not measure language ability but future studies should include this when exploring relationships among cognitive domains. Further, in an attempt to get a 'clean' measure of children's EF, I used the highest level passed as the dependent variable as opposed to the MEFS total or standardized score. These scores are composite measures of accuracy and reaction time, which would be biased against under-experienced tablet users, namely the younger participants who sometimes experience difficulties with dragging in the task.

## 2.5 Conclusion

In conclusion, the present study provides evidence that attentional control is related to executive control in children aged 24-72 months. Further, we now have evidence that measures of basic visual dynamics relate to aspects of cognitive development and executive control. The next step is to look at the neural mechanisms that underlie these relationships. These results set the stage for future work to measure looking dynamics in infancy in order to predict longer-term executive control outcomes, as well as working to understand how changes in brain function lead to differences in EF and effortful control over development. Importantly, understanding the mechanisms that underlie these relationships could provide empirical evidence that inform intervention efforts early in development.

# Chapter 3

# Early emergence of EF using neural and behavioral measures

## 3.1 Introduction

The goal of study 2 was to investigate the development of EF sub-components in 30-month-old toddlers using converging behavioral and neural measures. In the previous chapter I found important links between attentional control, working memory and effortful control. Here I aim to explore not only how each of these cognitive systems develops but to also inform our understanding of how they are related at two levels: brain and behavior.

Thus, in the present study participants completed the same tasks as in Chapter 2. I collected fNIRS data while participants completed a battery of eye tracking tasks that measure attention and working memory. In addition, participants completed the MEFS task at 30- and 42-months and parent-reported effortful control was collected at 42-months. An important goal of this chapter is to ask whether the previous results replicate in a sample of 30-month-old children.

The study focused on 30-month-olds because they are on the younger spectrum of chapter  2, which facilitates comparison across studies. Further, verbal instruction is possible with 30-month-olds thus, we can ask them to complete more complex measures of EF and EC. Importantly, there is great deal of development happening across a wide variety of domains during this age thus we can measure rudimentary forms of developing cognitive abilities and see if these measures are predictive of executive control 12 months later.

Previous work has shown that attentional control and WM have overlapping neural correlates (Duncan & Owen, 2000; Munakata et al., 2011), particularly early in development (Astle & Scerif, 2009; Scherf et al., 2006; Shing et al., 2010; Velanova et al., 2008). But little is known about how these networks overlap before the age of 4. In this study, I build on this work to explore if the component abilities of WM and attention rely on overlapping neural systems at 30 months and if individual differences in WM and attention at the behavioral and neural level relate to the emergence of later developing EF skills. By combining indices of brain function with behavioral measures, I elucidate relationships between functional activity and behavioral performance that shed light into the early processes that underlie later, more complex forms of EF.

## 3.2 Methods

### 3.2.1 Participants

The final sample included 76 30-month-old toddlers who participated in the study (*M* = 30.42 months, *SD* = 1.0 months, median = 30.6 months, 32 female). Participants had normal or corrected-to-normal vision. Color vision was assessed using a parent questionnaire developed by Ross-Sheehy to probe for a family history of color blindness. Other inclusion criteria included (1) uncomplicated birth between 37 and 42 weeks; (2) no reports of alcohol or illicit drug use during pregnancy; (3) no familial history of major psychiatric or depressive illness; (4) no preexisting neurological conditions or major head trauma. These criteria were confirmed during parental interviews at enrollment. Children were 91% white, 0.8% mixed race, and 0.01% african. 57% of mothers had completed a Bachelor's degree or higher. Median family annual income was £38,999 (range £5,200-£52,000).

An additional 15 toddlers were recruited to participate in the study but were not included in final analysis due to change in family circumstances (4), did not complete any activities (1), did not like fNIRS cap (4), no response to invites to schedule testing sessions (2), time commitments (2), and others withdrew without providing a reason (2). Figure 3.1 shows the distribution of data for each task.

This project was reviewed and approved by the UK NHS Health Research Authority Ethics committee (Protocol ID: IRAS 196063; PI: John P. Spencer). Parents signed an informed consent form. Children received a small toy of their choosing and a t-shirt for participating in each session. Parents received £20 per session. The data reported here are a subset of a longitudinal study looking into early brain and behavioral development where the goal is to understand typical neurocognitive development with an eye towards developing interventions that create environments that foster optimal child development and learning.

### 3.2.2 Procedure

Participants came in for three sessions: two lab sessions and an MRI session. In the lab sessions, participants completed the same battery of tasks as in Chapter 2 which were designed to tap attention, working memory, and hot

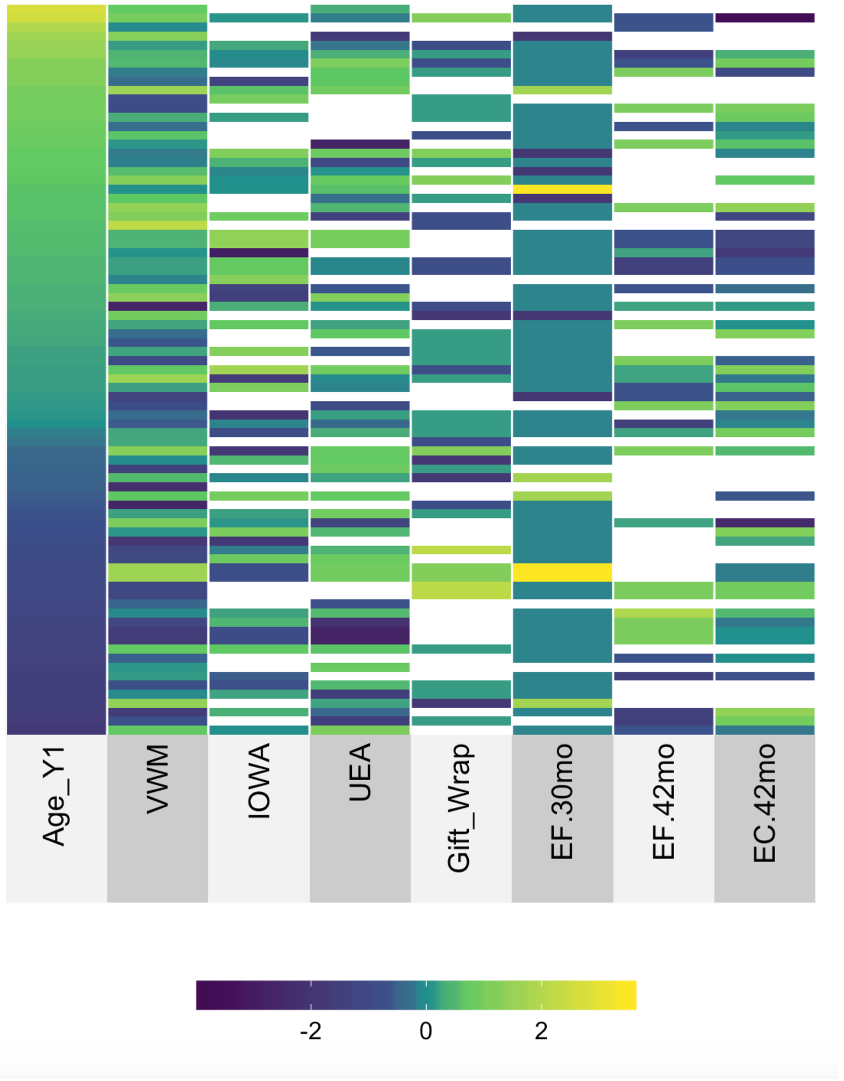

Figure 3.1: Data across tasks for each participant. Every row is a child. White portions depict missing data. Row-by-row participant data is scaled and color coded such that higher values in a given category are shown in lighter colors. For instance, darker blue in the Age_Y1 column reflect younger kids, while greener colors reflect older kids. Performance across tasks is similarly depicted, with greener colors meaning higher scores, and thus, better performance.

and cool executive functions. Typically, children completed the VWM task and one of the attention tasks in session one and another run of the VWM task, the other attention task, MEFS and Gift Wrap and Delay during the second session. The eye-tracking set up and pre-processing procedures were the same as before.

#### 3.2.2.1 Working Memory

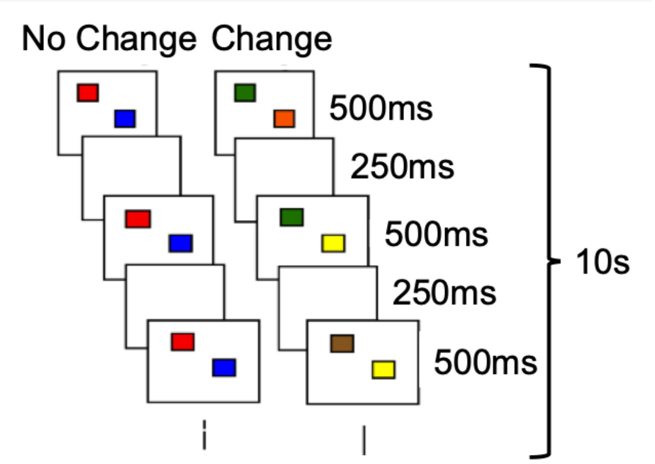

Figure 3.2: Trial schematic for the VWM-PL task.

##### 3.2.2.1.1 Visual Working Memory — two-streams Preferential Looking (VWM-PL) task.

I used a modified version of Ross-Sheehy et al. (2003). On each trial participants saw two side-by-side flickering displays composed of an array of colored squares. One side contained the change display and the other contained the no-change display. Each display contained colored squares that measured approximately 5 cm (w) by 5 cm (h). The set size (number of items in each array) was the same between the two displays and remained constant during the 10s trials. The colors of the squares were randomly selected from a set of nine colors: green, brown, black, violet, cyan, yellow, blue, red and white. The colors on a display were always different from each other but colors could be repeated between the displays (i.e., the same color could appear on both displays). The squares simultaneously appeared for 500ms and disappeared for 250ms. For the no-change display, the colors of the squares remained constant throughout the length of the trial. For the change display, one of the squares changed color after each delay. The changing square was randomly selected, and its color was derived from the set of colors not currently present in that display. Participants completed 12 randomized trials at each of three set sizes (2,4, 6). The displays containing the colored squares were 21cm (h) by 29.5cm (w) in projected size, separated on the screen by 21 cm, and subtended an average visual angle of 13.7 degrees.

#### 3.2.2.2 Attention

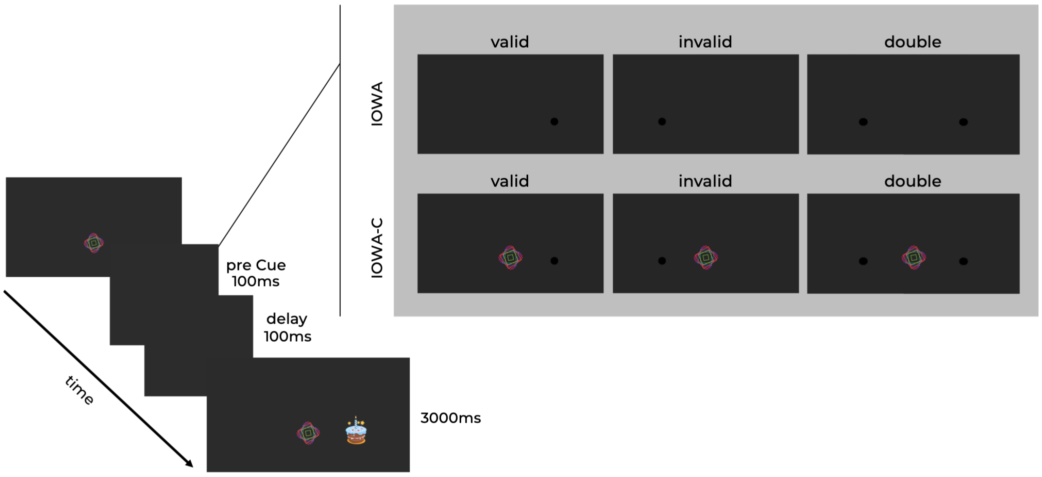

Figure 3.3: Trial schematic for the IOWA task. The sequence shows a IOWA: control trial. On the top right, all other possible trial types are shown. During IOWA-C trials, the attention getter remains on the screen for the duration of the trial.

**3.2.2.2.1 Infant Orienting with Attention task (IOWA)** The IOWA task follows the procedure described in Ross-Sheehy et al. (2015). Each trial commences with a central fixation, or attention getter (AG) in the form of a brightly colored dynamic zooming square animation. The attention getter appears until the participant fixates on it. This is followed by a precue interval of 200ms which is then followed by the target stimuli. The target stimuli could appear to the left or right of the AG and remains on screen for 3000ms. The spatial precue is a small black circle and the targets images were images of everyday objects. The precue was 1cm in projected size and subtended a visual angle of 0.6 degrees. The target images were between 5 and 7 cm in projected size and subtended an average visual angle of 3.4 degrees. The attention getter was 8cm in projected size and subtended a visual angle of 4.58 degrees. The distance between attention getter and target image was 25 cm.

There were three experimental conditions which contain a 100-ms spatial precue. The cues could appear (1) in the same location of the target (valid cue), (2) contralateral to the target (invalid cue), or (3) on both sides (double cue). An additional manipulation included competition (or overlap) trials, which essentially consist of the same experimental conditions but the central fixation stays on during the length of the trial. Reaction times and directional looking were recorded for each trial.

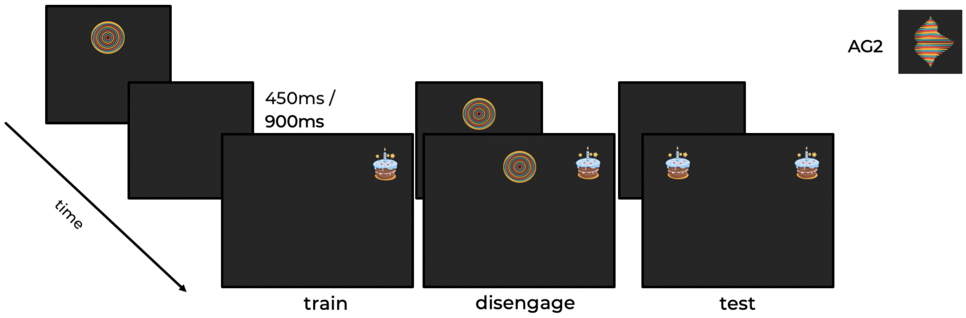

Figure 3.4: Trial schematic for the UEA task.

**3.2.2.2.2 Unified Executive Attention (UEA)** The Executive Attention task follows the procedure described in Johnson et al. (1991). Each trial begins with a centrally positioned attention getter (AG). One of two AG stimuli appears in a pseudo randomized sequence. The AGs are two distinct brightly colored animated gifs accompanied by distinct auditory stimuli. Trials commence when the participant fixates on the AG. There are three types of trials: training trials, test trials and disengage trials. On training trials, the AG goes off immediately after the fixation. There is a 900ms gap preceding the target onset, after which the target stimulus appears to the left or right side of the AG. The position of the target (left or right) is contingently associated with the AG presented at the beginning of the trial. The target stimuli are everyday objects (e.g., cake, balloons) . On test trials, the target appears on both sides of the screen regardless of which of the two AGs preceded it. Disengage trials are similar to training trials but the AG stays on throughout the trial. Thus, the contingent relationship between AG-target remains intact but both stimuli (i.e., AG and target) are presented simultaneously. The target images were between 5 and 7 cm in projected size and subtended an average visual angle of 3.4 degrees. The attention getter were between 10 and 10.5cm in projected size and subtended an average visual angle of 5.85 degrees. The distance between attention getter and target was 25 cm.

#### 3.2.2.3 Minnesota Executive Function Scale (MEFS$^{TM}$)

MEFS$^{TM}$ (Carlson & Zelazo, 2014) is an executive function iPad assessment based on the Dimensional Change Card Sort (DCCS, Zelazo, 2006). The task requires children to match and sort a variety of cards according to the dimensions of the target cards (e.g., size, color, shape). At each level, they have to follow one rule, and then switch to a new one. The difficulty increases as levels increase. The task has been found reliable (Beck, Schaefer, Pang, & Carlson, 2011) and valid (Carlson et al., 2013) in a sample of more than 5,000 children, and has been found to be predictive of school readiness and achievement over and above IQ (Carlson et al., 2013; Hassinger-Das et al., 2014). Figure 3.5 shows examples of the levels participants completed on this study. Participants completed this task at 30 and 42 months.

Look, I have these boxes here. This one has a horse on it, and this one has a duck on it. This is the duck game. In the duck game, all the ducks go in the duck box because that's where they belong! (tap + button)

Look, I have these boxes here. This one has a big elephant on it and this one has a little elephant on it. This is the elephant game. In the elephant game, all the big elephants go in the big elephant box and all the little elephants go in the little elephant box. (tap + button)

Look, I have these boxes here. This one has a frog on it and this one has a butterfly on it. This is the shape game. In the shape game, all the frogs go here and all the butterflies go here. (tap + button)

Look, I have these boxes here. This one is orange and this one is green. This is the color game. In the color game, all the orange ones go here and all the green ones go here. (tap + button)

Figure 3.5: Minnesota Executive Function Task (MEFS$^{TM}$

### 3.2.2.4 Gift Wrap and Delay

The Gift wrap and delay task has been extensively used and targets delay of gratification, a function of effortful control. The procedure follows Kochanska and Kim (2014) and Kochanska et al. (2000). Briefly, during the wrapping phase of the task, children waited –without peeking– while a gift was being noisily wrapped behind him or her (duration: 1 minute). During the delay phase, children waited in the seat –without touching the gift– while the experimenter left the room to get a bow (duration: 3 minutes). I followed the coding procedure of Kochanska and Kim (2014), where higher scores reflect a better effortful control.

During the wrapping phase, children's behavior was coded from 1 (turns fully around to look) to 5 (does not peek). During the delay phase, touching behavior was coded from 1 (opens gift) to 4 (never touches), and seat behavior from 1 (in seat for less than 30 sec) to 4 (in seat for more than 2 min). Peeking behavior was also coded for this phase following the same procedure as the wrapping phase. Additionally, latencies to peek, turn body around, touch the gift, and to leave seat were also coded. All coding was done using DataVyu Coding Software (D. Team, 2014).

#### 3.2.2.5 Behavioral Questionnaire

The very short form of the Children's Behavior Questionnaire (CBQ; Rothbart et al., 2001) was used for parent reports of temperament in preschool children. Parents completed the CBQ when participants were 42 months. In this study I only used factor scores for effortful control.

### 3.2.3 MRI

#### 3.2.3.1 MRI protocol.

Prior to scanning, children were allowed to fall asleep in a 'sleepy room' adjacent to the MRI room. To maximize success, we used these strategies: moved sleeping children into the scanner with minimal disturbance using transportation carts and immobilizers, added a sound-insulating insert to the MR bore (Ultra Barrier, American Micro Industries), electrodynamic headphones (MR Confon, Germany), and used customized 'quiet' imaging sequences (Deoni et al., 2011).

Participants were scanned during natural sleep. Each participant was imaged in a 3T Discovery 750w MRI scanner (GE Healthcare, Milwaukee, WI, USA) equipped with an 8-channel head coil. The imaging protocol consisted of localizer scans to properly position subsequent scans, and a 3D sagittal T1-weighted image with a 'Silenz' aquisition. This sequence consisted of a gradient-recalled echo readout with radial, center-out k-space filling and an inversion preparation pulse. Parameters were as follows: repetition time = 750 ms, echo time = 0.02 ms, inversion time = 650 ms, flip angle = 5°, receiver bandwidth = 244 Hz/voxel, field-of-view = 200 mm × 200 mm, matrix size = 200 × 200, and section thickness = 1 mm. The MRI session was completed after the acquisition of the 3D mcDESPOT protocol (Deoni, Dean, O'Muircheartaigh, Dirks, & Jerskey, 2012). This protocol consisted of: two balanced steady-state free precession (bSSFP) series with phase-cycling increments 0° and 180° to allow for correction of off-resonance artifacts (Deoni, 2011); a spoiled gradient-recalled echo (SPGR) series; and two inversion recovery SPGR scans for accurate estimation of the B1 transmit field. These components were acquired using optimized age-appropriate parameters, described previously (Deoni et al., 2012). Further, all mcDESPOT data were acquired in pure sagittal or coronal orientation, with a field-of-view adjusted for head size and participant orientation, and a matrix size and section thickness chosen to give consistent isotropic resolution of $1.7 \times 1.7 \times 1.7$ mm$^3$. To reduce acoustic noise, these scans were run with reduced gradient amplitudes and slew rates. This resulted in extended scan time. To minimize scan time, mcDESPOT data were acquired with a partial Fourier factor of 0.75 in $k_y$ and with an ASSET parallel imaging factor of 1.5. The full protocol lasted less than 45 minutes. A member of the research team was present in the scanner suite to monitor children at all times.

T1-weighted images were segmented using an optimized segmentation pipeline for young children and neonates. The procedure was as follows: (1) images were rotated into an axial orientation using 3dRotate in AFNI (Analysis of Functional Neuroimaging; W. Cox, 1996), (2) the resulting image was aligned to an age-matched template with an affine registration, (3) a skull mask derived from the template was used to remove irrelevant background noise, (4) the image was then bias corrected and (5) skull stripped. Next, (6) an individual brain mask was created. The mask was used to align the image to

ACPC orientation (7) by transforming it to the Talairach atlas and using only the rigid portion of the transform thus keeping the data in subject space. The resulting image was (8) median filtered to improve SNR prior to tissue classification (9). After classification, all tissue types, the skull and csf, were added into a 'hseg' image for further processing in AtlasViewerGUI (Aasted et al., 2015); HOMER2, Massachusetts General Hospital/Harvard Medical School, MA, U.S.A.). For participants without a useable T1-weighted image (n = 30), an age-matched (30mo) template was used and segmented following the steps above.

### 3.2.4 fNIRS

fNIRS is a non-invasive neuroimaging technique that uses light in the near-infrared spectrum to allow estimates of changes in hemodynamic response in the outer centimeter of the cerebral cortex (Scholkmann et al., 2014). During data collection, near-infrared light is emitted from a source fiber and received on a detector fiber placed several centimeters from the source (see figure 3.6. Changes in localized hemodynamic response (e.g., oxyhemoglobin or HbO, deoxyhemoglobin or HbR, and total hemoglobin or HbT) can be computed by monitoring changes in near-infrared intensity as it passes through the cortical tissue (Boas, Franceschini, Dunn, & Strangman, 2002; Jobsis, 1977).

This imaging technique has become the tool of choice to probe the neural processes that underlie multiple cognitive abilities in challenging populations such as infants, young children, and clinical patients who cannot be easily studied with fMRI (Boas, Elwell, Ferrari, & Taga, 2014; Lloyd-Fox, Blasi, & Elwell, 2010). In comparison to other imaging techniques, fNIRS has better temporal resolution than fMRI and better spatial resolution than EEG, and it is relatively more resistant to motion artifacts than both of the aforementioned techniques (for review and illustration of this comparison see figure 2 and dissusion in Lloyd-Fox et al., 2010). Importantly, given it's reliance on measuring the scattering and absorption of photons as they travel through cortical tissue, it offers limited depth resolution and cannot measure hemodynamic changes in subcortical regions.

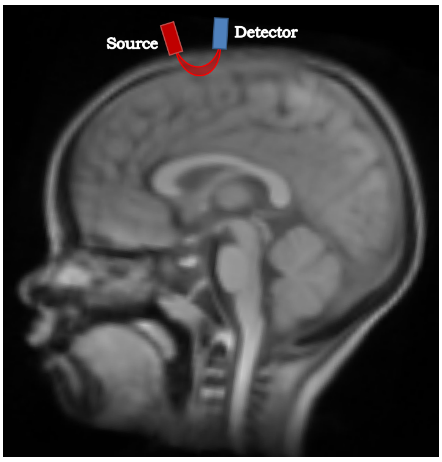

Figure 3.6: Schematic of fNIRS photon path overlaid over template MRI image. Photons travel from a laser fiber source (shown in red) to a detector fiber (shown in blue) through a 'banana shape' path with a depth resolution of half the source-detector distance.

At the beginning of each session, participants were fit with a custom EEG cap (EasyCap, EASYCAP GmbH, Germany) fitted with grommets to secure the optodes to the scalp. To improve optode to scalp coupling, hair was slightly moved using a hair clip prior to recording. fNIRS data was collected at 25Hz using a TechEn CW7 system (TechEn, Inc., MA, USA) with 690nm and 830nm wavelengths while participants completed the three tasks explained above (VWM-PL, UEA, and IOWA). Near-infrared light was delivered via 16 fiber optic cables (sources) to the participant's scalp and detected by 32 fiber optic cables (detectors) (see Figure 3.7). The lasers intensities were set to 12mW at the laser box. The intensities at the scalp ranged from 4.3mW to 6mW.

The probe was placed over the frontal, temporal, parietal, and occipital

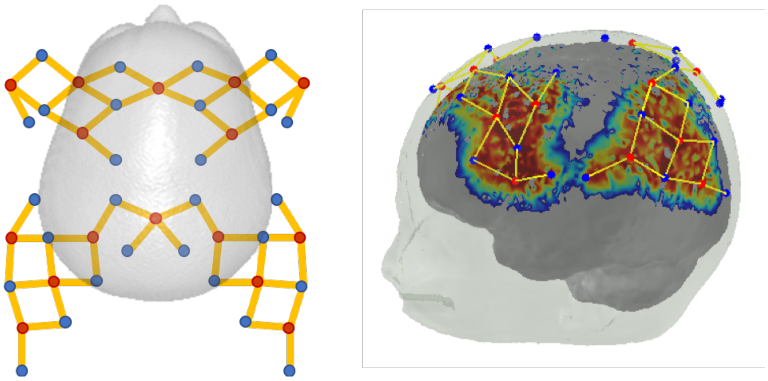

Figure 3.7: fNIRS probe array. In the left panel:Sources are marked with red circles; detectors are marked with blue circles; Channels are shown in yellow. In the right panel: Probe geometry laid over the sensitivity profile on an age-matched anatomical template.

cortex bilaterally to tap target regions of interest (for details on the probe geometry design see Wijeakumar, Spencer, Bohache, Boas, & Magnotta, 2015). The target ROIs were derived from a survey of the fMRI literature on VWM and EF (Wijeakumar et al., 2015; Shirer, Ryali, Rykhlevskaia, Menon, & Greicius, 2012) and included right Superior Intraparietal Sulcus (sIPS), bilateral Intraparietal Sulcus (IPS), bilateral Anterior Intraparietal Sulcus (aIPS), bilateral Ventral Occipital Cortex (VOC), bilateral Dorso-lateral Prefrontal Cortex (DLPFC), bilateral Superior Frontal Gyrus (SFG), bilateral Inferior Frontal Gyrus (IFG), Frontal Eye Fields (FEF), bilateral Middle Frontal Gyrus (MFG), bilateral Occipital (OCC) and bilateral Temporo-parietal Junction (TPJ). Additionally, the ROIs also included regions involved in the dorsal ventral fronto-parietal attention networks (for review, e.g.: Corbetta & Shulman, 2002; Corbetta, Patel, & Shulman, 2008).

To account for variations in head size across participants, source-detector distances were scaled relative to the head circumference using the 10-20 system (for details, see Table 5 in Wijeakumar et al., 2015). Source-detector distance in this study ranged from 23 to 26mm. Prior to the experimental task, infants were be fitted with a custom EEG cap that contained grommets to secure the fiber optics to the scalp. Optode positions were recorded in 3-dimensions using a Polhemus Patriot system (Polhemus, Vermont, USA) at the begining of the session allowing co-registration of fNIRS data with structural MR scans and co-registration of data across sessions. These data allowed us to align fNIRS data within the head volume, facilitating image-based analyses.

### 3.2.4.1 Pre-processing of fNIRS data.

fNIRS data were processed on a channel-by-channel basis using HomER2 (Huppert, Diamond, Franceschini, & David, 2009). Raw optical signals were demeaned and converted to optical density. Channels with low optical density (<75 dB; dB= $20 \cdot \log_{10}(y)$, where y is the intensity level measured by the CW7 system) were discarded from the analysis. Signal changes with an amplitude greater than 0.5au within 1s or with an SD greater than 50 were identified as motion artifacts. A targeted Principal Component Analysis (Yücel, Selb, Cooper, & Boas, 2014) was then applied for motion correction. Trials with remaining motion epochs after correction were discarded from analysis. Data were band-pass filtered (0.016-0.5 Hz) and the concentrations of HbO2, HbR, and HbT were computed using the modified Beer-Lambert Law (Strangman, Franceschini, & Boas, 2003). Recordings from source- detector pairs with short distances (~1 cm) were used as regressors to remove physiological fluctuations in the optical signal (Goodwin, Gaudet, & Berger, 2014; Saager & Berger, 2008; Zhang, Strangman, & Ganis, 2009). Data were analized with a general linear model (GLM). The model was run on each chromophore separately including regressors to capture stimulus duration for the conditions of interest as well as nuisance regressors (incliding the short-separation signal). Each regressor was convolved with a canonical gamma function (for details, see HomER2 'hmrDeconvHRF_DriftSS' function; HbO parameters: $\tau$=0.1, $\sigma$=3.0, T=10.0; HbR parameters: $\tau$=1.8, $\sigma$=3.0, T=10.0). This resulted in a channel specific $\beta$ estimate for each condition, and both chromophores (HbO and HbR) per participant.

#### 3.2.4.2 Forward Model.

When available, segmented subject-specific anatomy (T1-weighted images) was used to estimate a forward head model. If no T1-weighted image was present for a given participant, an age specific (30mo) atlas was used. The 'hseg' image resulting from the segmentation procedure explained above was imported into AtlasViewerGUI (Aasted et al., 2015); HOMER2, Massachusetts General Hospital/Harvard Medical School, MA, U.S.A.) to create 3D surface meshes. Digitized scalp landmarks and positions of all optodes (sources and detectors) were projected onto the anatomy and Monte Carlo simulations with 100 million photons were run to create sensitivity profiles for each channel for each participant (Figure 3.7). The head volumes and sensitivity profiles were then converted to NIFTI format. Participants' sensitivity profiles were summed together, thresholded at an optical density value of 0.0001 (see Wijeakumar et al., 2015), and transformed to a custom MNI space to create subject-specific masks. Participant-specific masks were then summed together to create a group mask. This mask was thresholded to create a final group mask such that it spanned voxels that contained data from at least 70% of the participants.

#### 3.2.4.3 Image Reconstruction.

I used a similar image reconstruction approach to those proposed by Ferradal, Eggebrecht, Hassanpour, Snyder, and Culver (2014) and Huppert, Barker, Schmidt, Walls, and Ghuman (2017). The methods for this approach have been discussed in previous work (Putt, Wijeakumar, Franciscus, & Spencer, 2017; Wijeakumar, Huppert, Magnotta, Buss, & Spencer, 2017; Putt, Wijeakumar, & Spencer, 2019; Jackson et al., 2019; Wijeakumar, Kumar, Delgado Reyes, Tiwari, & Spencer, 2019; Wijeakumar, Magnotta, & Spencer, 2017) and validated with other imaging modalities (e.g., fMRI; Wijeakumar, Huppert, et al., 2017; Huppert et al., 2017).

Briefly, the relationship between the hemodynamic response and delta optical density is given by:

$$\begin{bmatrix} d \cdot {\varepsilon^{\lambda 1}}_{HbO} \cdot \beta_{HbO} + d \cdot {\varepsilon^{\lambda 1}}_{HbR} \cdot \beta_{HbR} \\ d \cdot {\varepsilon^{\lambda 2}}_{HbO} \cdot \beta_{HbO} + d \cdot {\varepsilon^{\lambda 2}}_{HbR} \cdot \beta_{HbR} \end{bmatrix} = \begin{bmatrix} {\varepsilon^{\lambda 1}}_{HbO} \cdot F^{\lambda 1} & {\varepsilon^{\lambda 1}}_{HbR} \cdot F^{\lambda 1} \\ {\varepsilon^{\lambda 2}}_{HbO} \cdot F^{\lambda 2} & {\varepsilon^{\lambda 2}}_{HbR} \cdot F^{\lambda 2} \end{bmatrix} \cdot \begin{bmatrix} \Delta HbO_{vox} \\ \Delta HbR_{vox} \end{bmatrix}$$

where, $F$ is the channel-wise sensitivity volumes from the Monte Carlo simulations. $\Delta HbO_{vox}$ and $\Delta HbR_{vox}$ are voxel-wise relative changes in HbO and HbR concentrations and need to be estimated using an image reconstruction approach. We can re-write this equation as:

$$Y = L \cdot X$$

where,

$$Y = \begin{bmatrix} {\beta^{\lambda 1}}_{dOD} \\ {\beta^{\lambda 2}}_{dOD} \end{bmatrix}, L = \begin{bmatrix} {\varepsilon^{\lambda 1}}_{HbO} \cdot F^{\lambda 1} & {\varepsilon^{\lambda 1}}_{HbR} \cdot F^{\lambda 1} \\ {\varepsilon^{\lambda 2}}_{HbO} \cdot F^{\lambda 2} & {\varepsilon^{\lambda 2}}_{HbR} \cdot F^{\lambda 2} \end{bmatrix} and X = \begin{bmatrix} \Delta HbO_{vox} \\ \Delta HbR_{vox} \end{bmatrix}$$

To solve for $X$, I used Tikhonov regularization and the system in the above equation can be replaced by a 'regularized' system given by,

$$X = (L^T L + \lambda \cdot I)^{-1} L^T \cdot Y$$

where $\lambda$ is a regularization parameter that determines the amount of regularization and $I$ is the identity operator. Minimizing the cost function and solving for X yields voxel-wise maps of relative changes in concentration for each condition, channel, participant, and chromophore.

### 3.2.5 Analysis approach

#### 3.2.5.1 Task by Task analysis

For the eye-tracking tasks, data were pre-processed using Data Viewer (SR-Research, Ontario, Canada). Fixations with a duration less than 100ms were merged with a neighboring fixation, if the latter was within 1°. If neighboring fixations did not meet this criteria or were not temporally contiguous, the short fixation (<100ms) was discarded from analysis.

Trials were segmented into periods of interest (IP) using message-based events. Areas of interest (AOI) were set to be 50% bigger than target objects to account for calibration errors and drifts in the eye tracker. Sample reports were exported and raw gaze position was processed using the statistical package R (R. C. Team, 2017). Age in days was included in all analysis as a continuous variable.

**3.2.5.1.1 VWM-PL** Looking to the change side and non-change side at each point in time during the trial was aggregated into 100ms time bins, calculating the proportion of looks to the target (change side). To allow for the best possible statistical modelling of these time series data, the data was trimmed to start at 2500ms (at which point participants would have seen 3 full presentations) and end at 7500ms (the last two seconds of data are noisy because fewer participants maintained attention for the full 10s trial duration).

Change preference scores through time were fit with a binomial hierarchical model estimated with Laplace approximation using the glmmTMB package (Brooks et al., 2017) and eyetrackingR (Dink & Ferguson, 2016) in the statistical package R (R. C. Team, 2017). The model was fit with septic orthogonal polynomials of the time term (Mirman, 2014), that is, the data were modelled with time, time squared, up to time to the power 7, but scaled and centred so as to not be correlated with one another. In addition, the model contained fixed effects of Age in days (scaled and centered) and Load (low, medium, high). Five time terms and slope for load were nested as a random effect within participant, along with allowing each participant a random intercept for a maximally-specified model. The higher order polymomial time terms were excluded from the random effects structure to avoid difficulties with convergence.

Bootstrapped smoothed divergence analysis was performed to ascertain when during the length of the trials participant's looked significantly more to the changing side (>.50) vs the non-changing side. To do this, I used a modified function from the eyetrackingR (Dink & Ferguson, 2016) package. This allowed us to conduct a statistical test that operated over a smoothed version of the data (similar to Wendt et al., 2014). This method returned a list of divergences between participant's looking and a change preference criteria (set to >.50) based on time windows in which the 95% confidence intervals did not include 0 (i.e., p <.05).

**3.2.5.1.2 IOWA** I calculated Balanced Integration Scores (BIS) for each condition using code provided by Liesefeld and Janczyk (2019). BIS combines reaction times and error rates in a way that strongly attenuates speed-accuracy trade-offs. BIS scores were fit with a linear mixed model estimated by REML using the lme4 package (Bates et al., 2015) in R (R. C. Team, 2017). The model was fit with a three-way interaction of age in days, congruency condition (valid, invalid, double, control), and competition condition (competition, no competition), along with allowing each participant a random intercept for a maximally-specified model.

**3.2.5.1.3 UEA** To make sure participants learned the contingency between the AG and the subsequent target location, looking to the target item at each point in time during the trial was aggregated into 100ms time bins, from which I calculated the proportion of looks to the target.

For anticipatory looking trials, after the child fixated to the AG, if the child oriented to the target item during the anticipatory period (100ms into the gap period until 100ms after the onset of the target), it was coded as an anticipation (1); if they oriented only after the stimulus was presented, it was coded as non-anticipation (0); incorrect anticipations were coded as invalid (-1).

For disengagement trials, BIS scores were calculated following the procedure explained in Chapter 2.

**3.2.5.1.4 Behavioral Questionnaire** The Effortful Control factor scores were computed using the parent report Child Behavioral Questionnaire.

**3.2.5.1.5 MEFS** MEFS Highest Level Passed were correlated with age using a pearson correlation.

### 3.2.5.2 fNIRS analysis

For all tasks, fNIRS data were analyzed at the group level using ANOVA on the voxel-wise maps. The ANOVA had two categorical factors: condition (task-specific, see below), chromophore (HbO, HbR) and one quantitative covariate: age in days (centered and scaled). The analysis was limited to the voxels covered by the group-level mask (total number of voxels in the mask is 70618). The main effects and interactions from the ANOVA were thresholded at $p = 0.01$, corrected for family-wise errors using 3dClustSim (corrected at $\alpha$ <0.05, corresponding to a cluster size threshold of 42 voxels with a voxel resolution of 2 x 2 x 2 $mm^3$). Similar to Delgado Reyes et al. (in rev, in rev.), only effects with evidence of a main effect or interaction with chromophore are discussed.

To investigate brain-behavior relationships between the clusters with evidence of chromophore-related effects and behavioral variables of interest, I used Pearson's correlation or linear models.

## 3.3 Results

### 3.3.1 Behavioral Results

#### 3.3.1.1 VWM

Looking proportions were modelled with a hierarchical binomial model to examine the effects of Load and Age over time. The model utilized orthogonal septic polynomials of the time term to capture the model fit (Mirman, 2014). Fixed effects were tested with a Wald chi-squared test to assess the contribution of each parameter in reducing residual deviance of the model. The results indicate evidence for an interaction effect between the cubic, quartic and septic time terms and Age, an effect of all seven time terms and Load, as well as all 3-way interactions except the one including the hexic time term (see Table A.6). Thus, there is strong evidence that time course of looking to the change side varies by Load, and evidence that the amount by which the time course of looking to the change side varies at each Load differs across age. The model fit to the raw data can be seen in Figure 3.8.

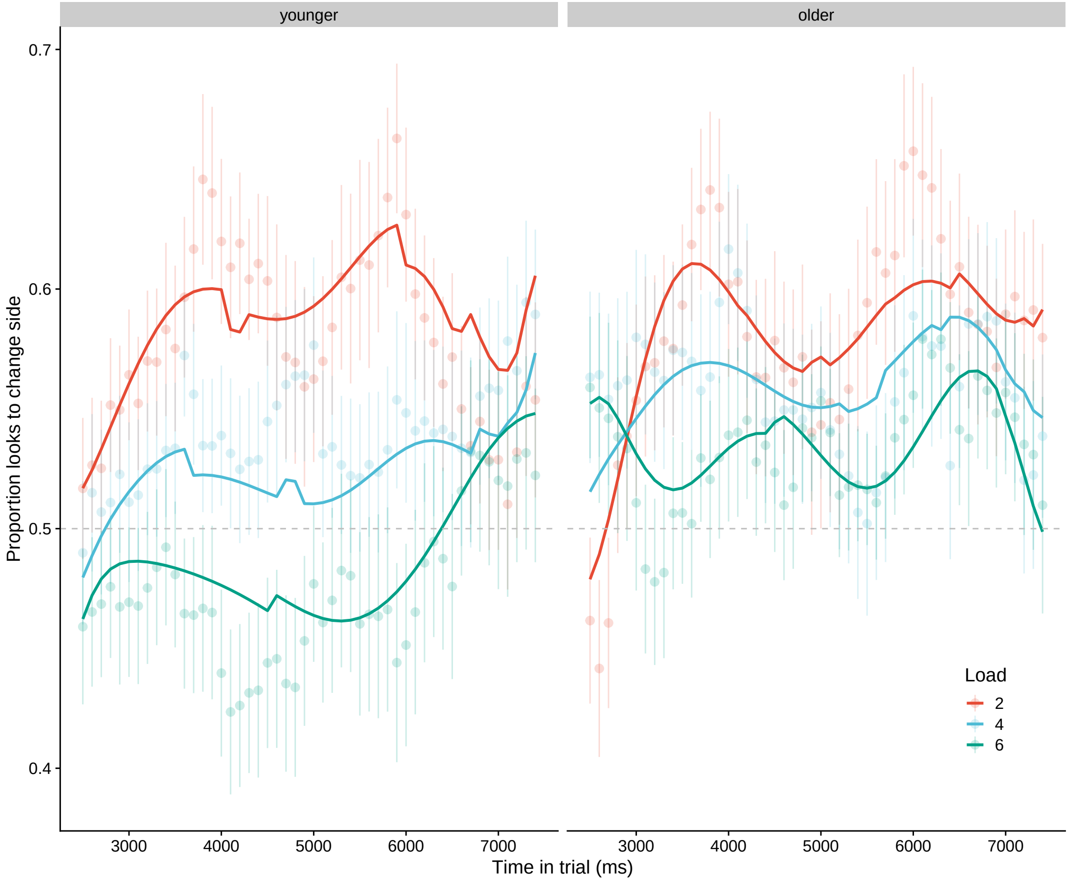

Figure 3.8: Model predicted proportion looking to change side by load by age. Grey dotted line depicts chance performance (0.50). Age in days was median split to facilitate visualization.

Proportion looking to the change side showed fluctuations through time across loads and age. Contrasting performance across the age range, it is evident that older participants preferred to look to the change side in all loads, while younger participants only showed a preference to look at the changing side on the lowest load.

Results from the divergence analysis show that participants' looking dynamics diverged from chance from 2900 to 8400 ms (see Figure 3.9). To create a VWM-PL score that I can move forward for further analysis, I calculated the change preference score in the 2500 to 7500ms window, i.e., the

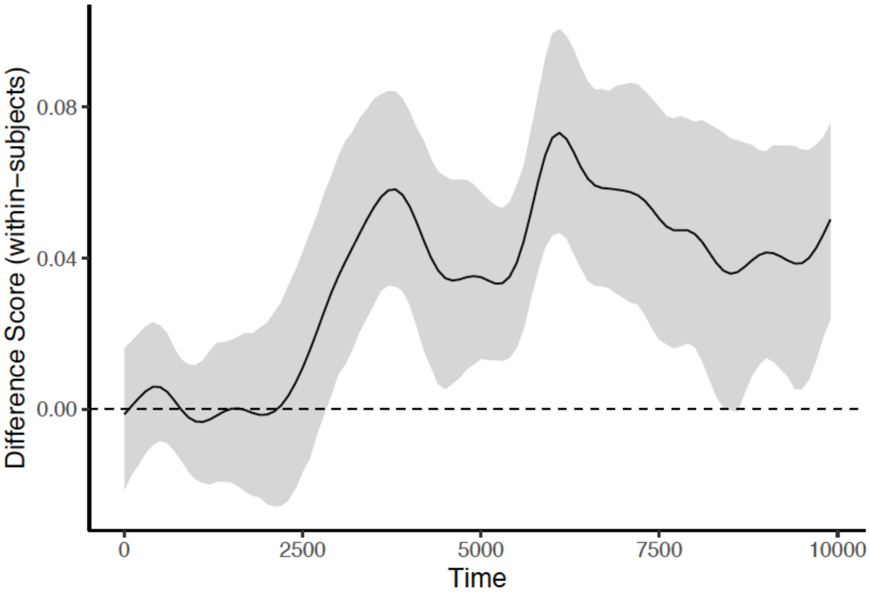

Figure 3.9: Divergence plot showing period of the trial where participant's looking is significantly different from chance (chance = .50).

same window I used to model the time series data (see Figure 3.10). Notably, this window largely falls inside the window identified in the divergence analysis. For younger kids, looking in the low load was significantly greater than chance ($p < 0.001$). Change preference in the medium load did not differ from chance, but looking in this condition was significantly greater than the change preference score in the high load condition ($p < 0.01$). Change preference in the high load did not differ from chance, but looking in this condition was significantly lower than the change preference score in the low load condition ($p < 0.001$). For the older participants, change preference in all three loads was significantly greater than chance low ($p < 0.001$), medium ($p < 0.01$), and high ($p < 0.05$). Contrasting change preference across loads for these children, change preference in the low load was significantly higher than change preference in the high load condition ($p < 0.028$). Table A.7 shows the comparisons against chance.

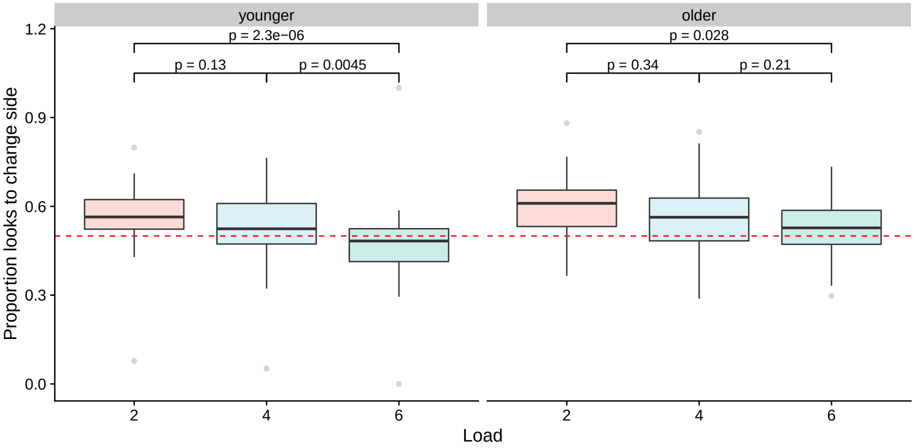

Figure 3.10: Change preference score across loads. Red dotted line depicts chance performance (0.50). Age in days was median split to facilitate visualization.

#### 3.3.1.2 IOWA

BIS scores were modelled with a linear mixed model to examine the effects of age, cue congruency (double, control, valid, invalid) and competition (competition, no competition). Fixed effects were tested with a Wald chi-squared test to assess the contribution of each parameter in reducing residual deviance of the model. The results indicate evidence for an effect of congruency and competition (see Table 3.1). Thus, there is stong evidence that the BIS score varies by congruency condition as well as competition condition. The model fit to the raw data can be seen in Figure 3.11.

Thus, as in previous research, performance was better in the no competition condition vs the competition condition ($p$ <0.001). Further replicating Ross-Sheehy et al. (2015) and the results from chapter 2, these results show that an invalid cue resulted in worse performance when compared to a valid cue ($p$ <0.001).

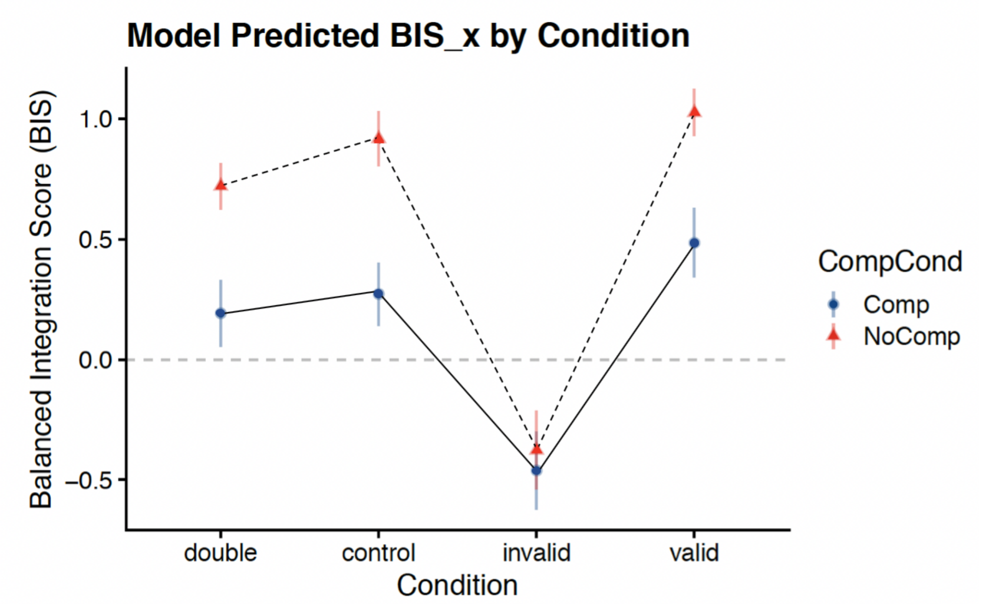

Figure 3.11: Model predicted BIS by condition. Light points show the raw data. While dark points shows the model predictions. Red triangles connected by the dashed line show the No Comp condition. Blue circles connected by the solid line show the Comp condition. Zero is the mean score across conditions.

Table 3.1: Regresion results using IOWA BIS score as the criterion.

| | **Chisq** | **Df** | **Pr(>Chisq)** | |
|---|---|---|---|---|
| (Intercept) | 20.2914 | 1 | <0.001 | *** |
| Age | 0.3039 | 1 | 0.581 | |
| Congruency Cond | 114.3927 | 3 | <0.001 | *** |
| Competiton Cond | 30.4885 | 1 | <0.001 | *** |
| Congruency Cond : Competition Cond | 7.2384 | 3 | 0.065 | . |
| Age : Congruency Cond | 6.7226 | 3 | 0.081 | . |
| Age : Competition Cond | 0.0026 | 1 | 0.960 | |
| Age : Congruency Cond : Competition Cond | 1.2323 | 3 | 0.745 | |

#### 3.3.1.3 UEA

**3.3.1.3.1 Contingency Learning** Upon examining the data, I noticed that there were some participants who had a proportion looking at target of <.10. This could mean that the participants were not ’on-task’ or it could also be due to track-loss. To ensure I were only looking at participants who were ’on-task’, I filtered out participants with a proportion looking to the target <.10

from the rest of the analysis.

Figure 3.12 shows the proportion looking to the target item through time on test trials. The figure shows that participants looked at the target item within the first second after the onset of the target. However, they tended to look back and forth between items for the rest of the trial length. Thus, they may have learned the contingency between target and attention getter but their visual dynamics were impacted by the appearance of the distractor item.

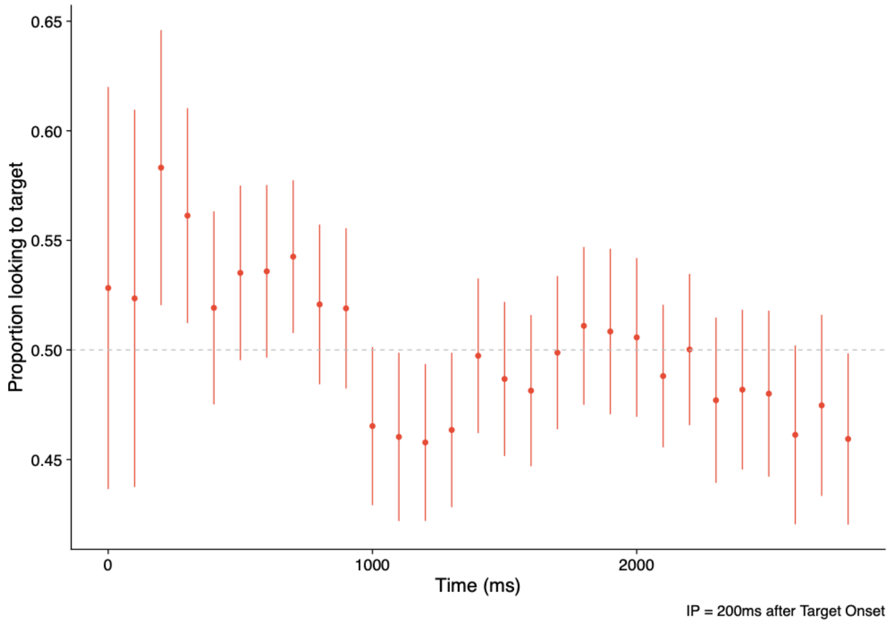

Figure 3.12: Proportion looking to target item on 'test' trials.

**3.3.1.3.2 Anticipatory Looking** Figure 3.13 shows participants performance in Anticipatory Looking trials. Participants probability to produce an anticipatory look was around 50%, which is consistent with results from participants in this same age range in Chapter 2.

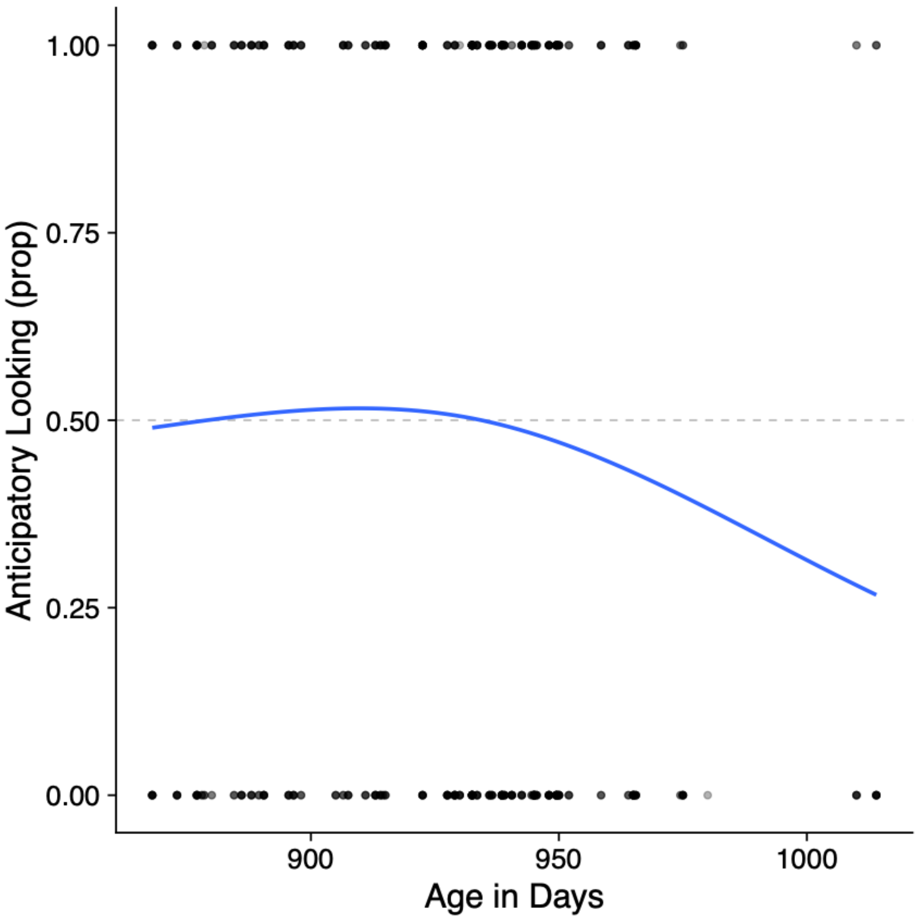

Figure 3.13: Proportion of anticipatory looks by age.

**3.3.1.3.3 Disengagement** Figure 3.14 shows participants performance in disengagement trials. There is a slight trend that suggests that participants became more efficient as they got older. Even though it is hard to compare two independent sets of standardize scores, results from this study are consistent with participants in the same age range from Chapter 2.

#### 3.3.1.4 Gift Wrap

Based on the results from chapter 2, I focused on the peeking score during the wrapping phase of the task. Figure 3.15 shows participant peeking score during this phase of the Gift Wrap task. These results are consistent with the

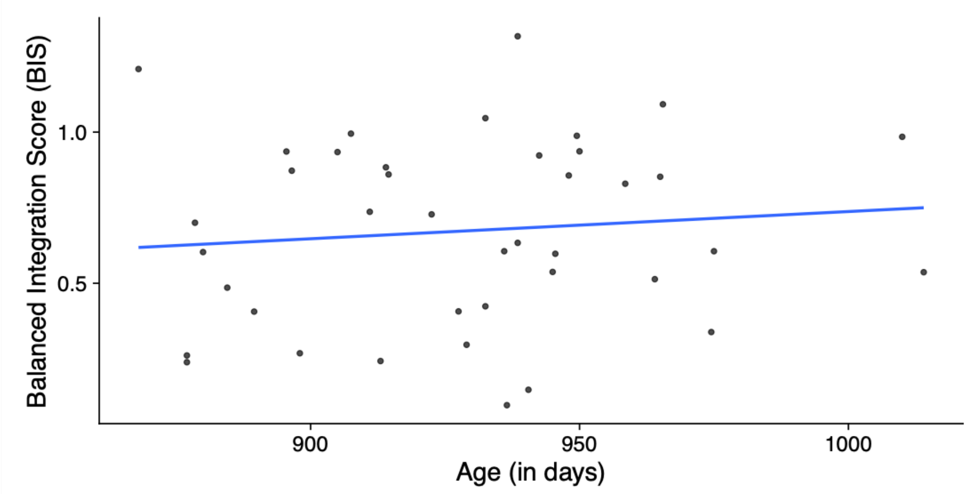

Figure 3.14: Disengagement BIS by age.

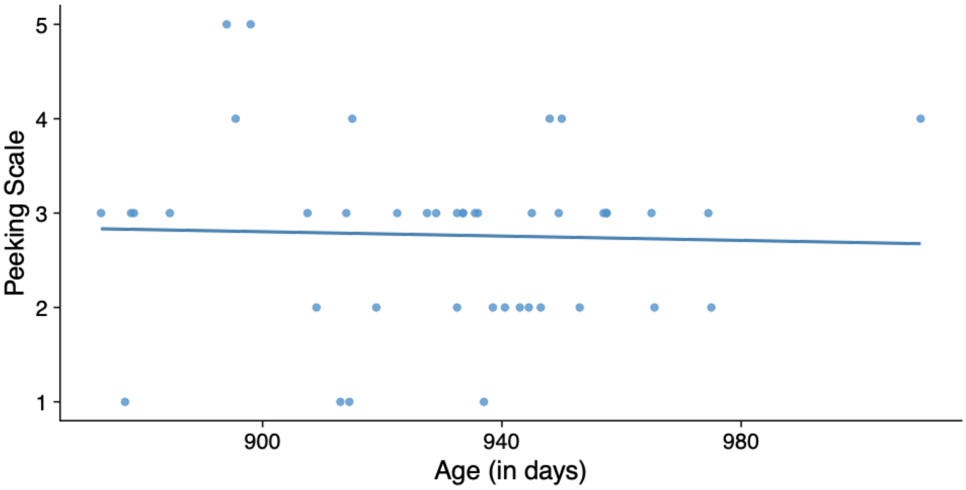

Figure 3.15: Gift Wrap peeking score.

results from the previous chapter in that participants in this age range were among the 2-3 levels of the peeking scale.

#### 3.3.1.5 MEFS

Figure 3.16 shows participant MEFS Standard Scores at their 30- and 42-month visits. The figure depicts individual differences in executive function development from 30 to 42 months. Importantly, these results are also consistent with age-matched participants in the previous chapter. The correlation

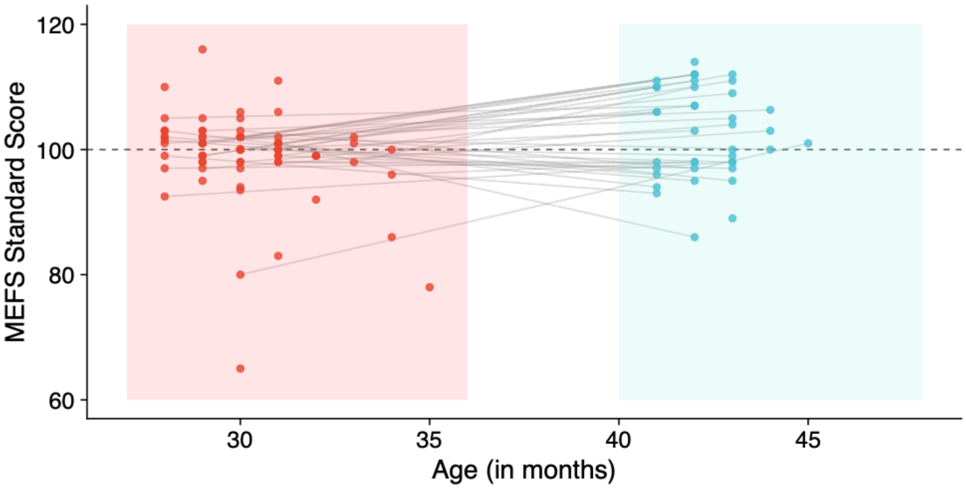

Figure 3.16: MEFS standard score at 30- and 42-months visits. Line depict the within subject change in EF across year 1 (30 months) and year 2 (42 months). Shading depicts year-by-year data: year 1 is depicted in red; year 2 is depicted in teal.

between EF at 30 months and EF at 42 months was not significant, p >0.1.

#### 3.3.1.6 Temperamental Effortful Control at 42 months visit

Figure 3.17 shows parent-reported effortful control by gender. As in the previous chapter, girls seem to have a higher effortful control than boys. This difference seems to be more noticeable as children get older.

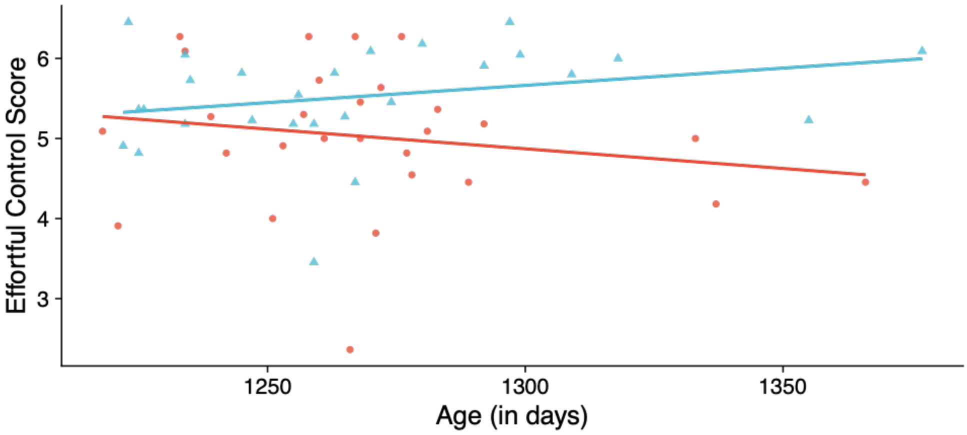

Figure 3.17: Effortful Control by Gender.

### 3.3.1.7 Relationships among tasks

Uncorrected correlations between study measures are shown in Figure 3.18. Results show that performance in the high WM load was negatively correlated with performance in the low (r(74) = -0.30, p <0.01) load, medium (r(74) = -0.24, p <.05) load, and with effortful control at 42 months (r(74) = -0.31, p <0.05). Working memory in the low load was negatively related to performance in the invalid condition in the IOWA task (r(74) = -0.34, p <0.05). Attentional disengagement was positively correlated with working memory performance in the medium load (r(74) = 0.30, p <0.05). Figure 3.19 shows scatter plots for these correlations.

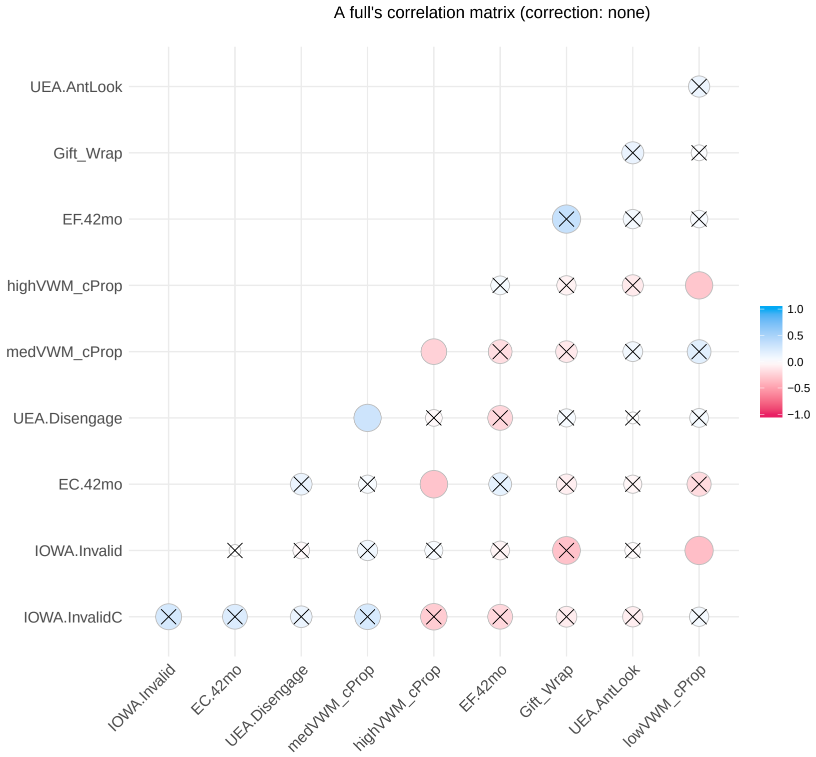

Figure 3.18: Correlation matrix shows the correlations (uncorrected) across all variables. Blue depicts positive correlations and red depicts negative correlations. The 'x' denotes correlations that were not significant. The size and intensity of the color of the circle denotes the strength of the relationship.

Based on the path analysis results form Chapter 2, I explored the relation-

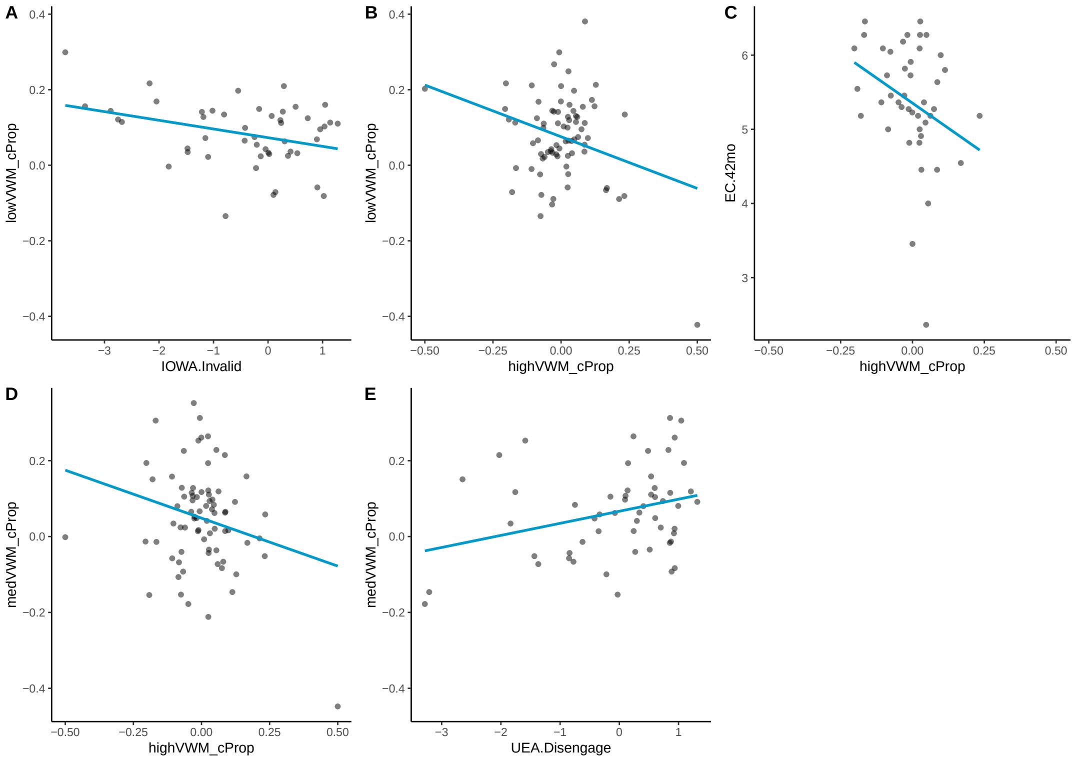

Figure 3.19: Scatter plots of correlations (uncorrected). Note that these correlations did not survive correcting for multiple comparisons.

ship between 30-month old measures and effortful control at 42 months using a linear model. Results show that age ($\beta$ = -2.16, p = 0.003), efficiency of disengagement in the UEA task ($\beta$ = 0.46, p = 0.010), and the interaction between age and proportion of anticipatory looks in the UEA task ($\beta$ = 4.36, p = 0.003) at 30 months are predictors of effortful control at 42 months. This replicates and extends the results from Chapter 2.

## 3.3.2 fNIRS Results

### 3.3.2.1 VWM-PL

A group-level ANOVA was run on the voxel-wise maps generated from fNIRS image reconstruction (see Methods) with Age as a quantitative between-subjects factor and load (2, 4, 6) and chromophore [Hb] (HbR, HbO) as within-subjects

Table 3.2: Regression results using effortful control at 42 months as the criterion

| | **Effortful Control at 42 mo** | | |
|---|---|---|---|
| *Predictors* | *Estimates* | *CI* | *p* |
| (Intercept) | 5.28 | 4.28 – 6.27 | **<0.001** |
| Age_Y1 | -2.16 | -3.29 – -1.03 | **0.003** |
| lowVWM | -1.65 | -5.06 – 1.76 | 0.361 |
| highVWM | -4.67 | -9.05 – -0.29 | 0.058 |
| IOWA_Invalid | -0.15 | -0.41 – 0.11 | 0.278 |
| UEA_AnticipatoryLook | 0.56 | -0.96 – 2.09 | 0.483 |
| UEA_Disengagement | 0.46 | 0.16 – 0.76 | **0.01** |
| IOWA_InvalidComp | -0.15 | -0.41 – 0.11 | 0.284 |
| EF_30mo | -0.26 | -0.9 – 0.38 | 0.439 |
| Age_Y1:lowVWM | -0.47 | -4.08 – 3.15 | 0.805 |
| Age_Y1:highVWM | 3.22 | -0.3 – 6.74 | 0.099 |
| Age_Y1:IOWA_Invalid | 0.07 | -0.32 – 0.46 | 0.738 |
| Age_Y1:UEA_AnticipatoryLook | 4.36 | 2.05 – 6.68 | **0.003** |
| Age_Y1:UEA_Disengagement | 0.08 | -0.23 – 0.40 | 0.607 |
| Observations | 26 | | |
| $R^2$ / $R^2$ adjusted | 0.802 / 0.588 | | |

factors. The main effects and interactions from the ANOVA were thresholded at $p$ <0.01, and corrected for family-wise errors ($\alpha = 0.05$; see Methods). Only statistically significant main effects and interactions that included chromophore are discussed (i.e., Hb, Age x Hb, Load x Hb, and Age x Load x Hb effects). A significant chromophore effect reveals a good signal-to-noise ratio as the canonical hemodynamic response shows an anticorrelation between HbO (+) and HbR (-).

The ANOVA results are reported in Table A.8. Figure 3.20 and figure 3.21 show the combined ANOVA results. fNIRS clusters overlapped with ROIs from the VWM network previously identified in fMRI studies with adults, namely IFG, VOC, IPS, and MFG.

The spatial organization of the network engaged in the present study is consistent with previous studies investigating the early development of VWM from 4 months to 2 years (Delgado Reyes et al., in rev) and VWM in under-resourced environments (Wijeakumar et al., 2019). Figure 3.20-B illustrates changes in the hemodynamic response in l-VOC as a function of age. Younger children had greater neural activity that older children in this region. Indeed, older children seem to show an inverse hemodynamic response in this cluster. Panel A shows brain activity in l-MFG. This cluster showed a canonical pattern with HbO greater than HbR.

Figure 3.21 illustrates how brain activity changed as a function of the interaction between memory load and age for clusters in the frontal, parietal and occipital cortex. In the frontal cortex, namely rIFG, younger participants show activation at load 2 and 4, and then the activity drops off at load 6, while older participants showed an increase in hemodynamic response from load 2 to 4 but a decrease at load 6. The activity observed in older children is consistent with fMRI studies suggesting an increase in frontal engagement at higher set sizes to support WM performance (see Edin et al., 2009). Younger children also showed this pattern, but they need more IFG support at load 2. Thus, for both younger and older children, IFG is supporting performance for within-capacity loads. When capacity is exceeded, IFG activity drops off. In the occipital cortex, results show a notable decrease in oxyhemoglobin as a function of load in l-VOC for the older children, while younger children show the same pattern from load 2 to 4, but then show an increase in brain activity at load 6. This increase in brain activity in super-capacity loads is consistent with previous research showing an increase in the hemodynamic response as the loads increase (Buss et al., 2014). Activity in the r-IPS followed a similar pattern to activity in l-VOC for the younger children, while older children had little to no activation in this region.

Next, I examined whether the significant clusters from the omnibus ANOVA were related to individual differences in task performance. I ran a linear model predicting neural activity in the cluster of interest with age, proportion looking to the change side, and load as predictors. Activity in the left VOC was predicted by participants behavior in the task. All the following relationships between neural activity and performance in the task were localized to the same VOC cluster (shown in Figure 3.21). Figure 3.22-A shows a forest plot with the standardized model estimates. This plot depicts a summary of the model estimated coefficients and confidence intervals (CI). Estimates whose CI do not overlap with 0, are significant effects. Focusing on effects including participant's performance in the task, figure 3.20-B shows the main effect of proportion looking to the change side. Better performance in the task resulted in decreased activation. Figure 3.20-C shows a similar pattern such that better performance in the task in the highest load leads to less brain activity in VOC. These results suggest that children who perform better in the task have more efficient activation in l-VOC.

Figure 3.21-A shows that these effects are qualified by an interaction with age. In particular, older children who performed better in the task, showed a relative increase in neural activity. Finally, figure 3.23-B shows both a dependency on age and load. Specifically, in the lower load conditions, older children who did better in the task have greater brain activity in VOC. In the highest load, however, this effect is reversed with a steep reduction in brain activity for older participants with a high proportion looking to the change side. Thus, increases in l-VOC activation supported good performance in older children at the low loads with a drop-off in activation at the highest load, suggesting a task-specific 'tuning' of neural activation to the demands of the task.

Previous research has revealed that L-VOC is a site for color representations (Brewer, Liu, Wade, & Wandell, 2005; Wade, Brewer, Rieger, & Wandell, 2002). In this context, the results reported here suggest a link between increased neural activity, changes in the neural representation of colors, and enhanced performance in the task. Further, these results suggest that VOC is becoming more tuned to VWM performance over development. Results showed a stronger load-dependent VOC responses in the good performers, with increasing activation at low and medium loads that are within-capacity, and a drop off of activation at high loads when the set size exceeds capacity. Thus, VOC may be strongly reflecting VWM capacity in the good performers. Moreover, the load dependent effect we see in r-IFG shown in figure 3.21 indicates that this region is supporting WM performance at the medium load, particularly in older children.

**3.3.2.1.1 Relationship to Effortful Control at 42 months** Next, I examined wether brain activity in these clusters was related to effortful control at 42 months. I focused on VOC, IFG and IPS given the effects of age and load seen in these clusters and the relationship to behavior in the VWM task (e.g., VOC). I ran a linear model predicting effortful control with age, beta, and load as predictors. I focused on the beta main effect, or interactions with it. There were no significant relationships between brain activity in VOC or IPS and effortful control. However, the interaction between activation in IFG and age was related to effortful control such that younger children who showed a higher IFG activation, had higher effortful control (see figure 3.24). Recall that for both younger and older children, IFG is supporting performance for within-capacity loads in the WM task.

#### 3.3.2.2 IOWA

A group-level ANOVA was run on the voxel-wise maps generated from fNIRS image reconstruction (see Methods) with Age in days as a quantitative between-subjects factor and cue congruency (valid, invalid, double, control), competition (competition, no competition) and chromophore [Hb] (HbR, HbO) as within-subjects factors. The main effects and interactions from the ANOVA were thresholded at $p$ <0.01, and corrected for family-wise errors ($\alpha$ = 0.05; see Methods). Only statistically significant main effects and interactions that included chromophore are discussed (i.e., Hb, Age x Hb, Congruency x Hb, Competition x Hb, Age x Cue Congruency x Hb, Age x Competition x Hb, and Age x Cue Congruency x Competition x Hb effects).

The ANOVA results are reported in Table A.9. Figures 3.25, 3.26 and 3.27 show the combined ANOVA results. fNIRS clusters overlapped with ROIs from the adult fMRI literature (see Methods), namely bilateral DLPFC, TPJ, aIPS, MFG, IPS, and close to VOC.

Figure 3.25 illustrates how brain activity changed as a function of the interaction between cue congruency, competition and age for clusters in the frontal, parietal and temporal cortex. In the frontal cortex, we saw differential activity as a function of competition and cue congruency. Notably, in the l-DLPFC, there was an increase in neural activity over development in the control, no competition condition. In the invalid competition and double competition conditions, activity was relatively higher (vs. no competition) but decreasing over development. Activity in the valid competition condition also showed a relative increase but less than this same change in the no competition condition.

In the r-DLPFC, results show a sharper decrease in activity during the double no competition condition over development in comparison to the l-

DLPFC. In the competition condition, this same condition showed sustained activity over development. Moreover, there was an increase in neural activity in the invalid competition condition while activity in the valid and control conditions decreased as a function of age. Moving to the left posterior cortex, we saw similar decrease of neural activity in the invalid no competition condition both in l-TPJ and l-aIPS. Notably, in l-aIPS, we saw an increase in activity on the control no competition condition over development. A similar change was observed in the double no competition condition in l-TPJ. In the competition condition, neural activity decreased rapidly over development in the double condition in both regions of the parietal cortex. In l-TPJ, there was an increase in brain activity in the valid condition while a similar but slightly attenuated hemodynamic change was seen in the invalid on l-aIPS. Thus, these results show dynamic changes over the course of this short period of development as a function of competition and cue congruency in regions previously identified as part of the executive control network and the visuospatial networks (Shirer et al., 2012).

Figure 3.26 illustrates how neural activity changed as a function of Competition and Age. Clusters in bilateral MFG showed an increase in both chromophores in the competition condition. This effect is bigger in the younger kids and in the l-MFG. Figure 3.27-A illustrates changes in neural activity over development in the temporal, parietal and occipital cortices. In the parietal cortex, there is an increase in both chromophores for the younger children while the older kids show a canonical response. In the occipital cortex, young children show deactivation while older children had an increase in both oxy- and deoxy-hemoglobin signals. In the temporal cortex, we see a parallel increase in both chromophores, with a higher signal change for the younger children. Figure 3.27-B shows task-relevant neural activity in the r-DLPFC.

The spatial location of these clusters is also consistent with the dorsal and ventral attention systems (Corbetta & Shulman, 2002; Corbetta et al., 2008).

In all, the results show robust engagement in regions of the brain previously shown to be important for attentional processes. Next, I wanted to see if this activity was related to participants' behavior in the task. As before, I focused on clusters that showed dynamic changes as a function of the variables of interest. I first looked at the frontal cortex. Recall that we had bilateral activation in DLPFC. Analyses of individual differences in performance showed that activity in r-DLFPC was related to participants' behavior in the task. Figure 3.28-A shows a forest plot with standardized estimates from a model predicting brain activity in the r-DLPFC with behavior. The effects were mostly driven by the control condition. Recall that the control condition is the one where no cue precedes the onset of the target thus there is no spatial information that could be used to make a rapid eye movement to the target object. Results show that better performance in the control condition engaged this region (see figure 3.28-B). Moreover, younger children who performed well in the task engaged r-DLPFC, while those who showed impaired performance tended to suppress activity in this region (see figure 3.28-C). The difference in brain activity in r-DLPFC across conditions decreases over development but this is mediated by children's performance in the task such that it is more evident in children who didn't do well in the task.

In the parietal cortex, activity in l-aIPS was also predicted by participants' behavior in the task (see figure 3.29 and 3.30). Figure 3.29-A shows the forest plot with standardized model coefficients and confident intervals. Figure 3.29-B show the main effect of BIS. This main effect shows that activity in this region decreased with better performance in the task. Figure 3.29-C shows the interaction between age and BIS score. Results show that younger children who performed poorly in the task had higher activation in aIPS. In contrast, older children who performed well in the task activated this region. The interaction between BIS and Cue Congruency show that better performance leads to a decrease in activation primarily in the valid (easier) condition (see Figure 3.30-A). Thus, poor performers are over-activating in the 'easy' condition and failing to show activation in the harder conditions. Better performers, on the other hand, show a relative increase in brain activity in the invalid and control conditions (see figure 3.30-A), which are the more difficult conditions in this task.

The interaction between age, competition and BIS was also a significant predictor of neural activity in this region such that, within participants who performed well in the task, older children showed a small decrease in activation in competition trials relative to no competition (see figure 3.30-B). By contrast, young children who performed poorly in the task show an over-activation in aIPS in no competition vs. competition. The age, BIS and cue congruency effects was mostly driven by the valid condition. Again, we see that within the younger children, the worse performers show over activation of this region (see figure 3.30-C). Further, the 4-way interaction between age, competition, cue congruency and BIS highlights that worse performers are over-activating aIPS in easy conditions (e.g., valid, no comp) and failing to show activation in the harder conditions (see figure 3.30-D). Importantly, older participants who show better performance in the task show an increased activation in the invalid and control competition conditions.

In all, these results show, for the first time, which regions of the brain participants use to support performance in this task. Importantly, participants behavior was predictive of brain activity in key regions previously liked with attentional systems. Context-specific activity in the l-aIPS appears to provide a meaningful index of performance in this task. In particular, children who aren't so good at the task have to work hard in the 'easy' conditions over development while children who do well work hardest in the 'hard' conditions.

**3.3.2.2.1 Relationship to Effortful Control at 42 months** Next, I examined wether brain activity in these clusters was related to effortful control at 42 months. I focused on bilateral DLPFC, left TPJ, left aIPS, and right IPS given the effects of age, cue congruency and competition seen in these clusters and the relationship to individual differences in behavior (e.g., r-DLPFC, l-aIPS). I ran a linear model predicting effortful control with age, beta, cue congruency and competition as predictors. I focused on the beta main effect, or interactions with the beta factor. Results show that brain activity in bilateral DLPFC and left TPJ are predictive of effortful control at 42months.

Beginning with l-DLPFC, the interaction between cue congruency and activity in this region was predictive of effortful control. In particular, increased brain activity in the control condition was predictive of higher effortful control (see figure 3.31-B). The interaction between competition and brain activity in this region was also predictive of effortful control such that increased brain activity in the competition condition was predictive of lower effortful control (see figure 3.31-C). Further, the interaction between age, cue congruency and brain activity in l-DLPC was predictive of effortful control. The effect was driven by the competition condition such that higher brain activity in this region was predictive of lower EC but this effect is attenuated for the older children compared to younger children (see figure 3.32-A). Figure 3.32-B shows the interaction between age, cue congruency and brain activity. This result was driven by the double condition. Results showed that in the double condition, higher activity in this region was predictive of higher effortful control (see figure 3.32-B). Finally, the interaction between between cue congruency, competition and brain activity in this region was also predictive of effortful control at 42 months. This result was driven by the control and invalid conditions. In both of these, higher brain activity was predictive in the competition condition was predictive of lower effortful control (see figure 3.32-C).

Activity in r-DLPFC, was also predictive of effortful control. Within this region, higher brain activity led to higher effortful control particularly for older children (see figure 3.33-B). That is, older children, who had lower brain activity in this region had lower effortful control. Figure 3.33-C depicts the interaction between cue congruency, age and brain activity. Results show that, in older children, higher brain activity in the double condition was predictive of higher effortful control.

Further, activity in l-TPJ was predictive of effortful control at 42 months. Similar to what we saw in r-DLPFC, the overall result in this region is that higher brain activity is predictive of higher effortful control. Figure 3.34-A shows the standardized model estimates with confidence intervals. Figure 3.34-B shows that higher brain activity in the competition condition leads to higher effortful control. Figure 3.34-C shows that within older children, higher brain activity in this region predicts better effortful control. Figure 3.35-A shows that in the competition condition, older kids who had higher brain activity in this region, had higher effortful control. This effect is also present in the no competition condition however, the slope of the effect is steeper for the competition condition. In figure 3.35-B we can see that across all conditions, higher brain activity lead to higher effortful control. Further, figure 3.35-C shows that higher brain activity in invalid and double competition conditions are predictive of higher effortful control. Finally, figure 3.35-

D shows the interaction between age, cue congruency, and brain activity. This effect is driven by the interaction between age and double condition, such that in this condition, higher brain activity is predictive of higher effortful control but younger kids showed overall higher EC than older children.

Recall that behavioral performance in the task was not related to effortful control. Further, effortful control is not related to age. Seems like the extent to which the hardest conditions in this task (e.g., control, invalid, double) engage the brain serves as an index of individual differences in effortful control at 42 months.

### 3.3.2.3 UEA

**3.3.2.3.1 Anticipatory looks** A group-level ANOVA was run on the voxel-wise maps generated from fNIRS image reconstruction (see Methods) with Age as a quantitative between-subjects factor and AL (Anticipatory Look/No Anticipatory Look) and chromophore [Hb] (HbR, HbO) as within-subjects factors. The main effects and interactions from the ANOVA were thresholded at $p$ ¡ 0.01, and corrected for family-wise errors ($\alpha = 0.05$; see Methods). Only statistically significant main effects and interactions that included chromophore are discussed (i.e., Hb, Age x Hb, AL x Hb, and Age x AL x Hb effects).

The ANOVA results are reported in Table A.10. The top panels in figure 3.36 show the combined ANOVA results for this task. There was a relative increase in brain activity in l-IFG as a function of age such that older children showed a higher activity in this region(see figure 3.36-A). An Age x Anticipatory Looking x Chromophore effect showed a small relative change in brain activity in l-STG such that older children who produced anticipatory looks showed an increase in HbR (see figure 3.36-B). These clusters were not related to individual differences in task performance.

**3.3.2.3.2 Disengagement** A group-level ANOVA was run on the voxel-wise maps generated from fNIRS image reconstruction (see Methods) with Age as a quantitative between-subjects factor and Disengagement (Disengage/No Disengage) and chromophore [Hb] (HbR, HbO) as within-subjects factors. The main effects and interactions from the ANOVA were thresholded at $p < 0.01$, and corrected for family-wise errors ($\alpha = 0.05$; see Methods). Only statistically significant main effects and interactions that included chromophore are discussed (i.e., Hb, Age x Hb, Disengage x Hb, and Age x Disengage x Hb effects).

The ANOVA results are reported in Table A.10. The bottom panels in figure 3.36 shows the combined ANOVA results for the disengagement condition. We saw task related activity in l-M/SFG and l-TPJ. A linear model between neural activity in TPJ and behavioral performance showed that older children who did better in the task (higher BIS scores), had higher activity in this region compared to younger children (see figure 3.37).

**3.3.2.3.3 Relationship to Effortful Control at 42 months** Next, I examined wether brain activity in these clusters was related to effortful control at 42 months. I focused on IFG, STG, TPJ, and M/SFG given the effects of age, condition (e.g., anticipatory looking, disengagement) seen in these clusters. I ran a linear model predicting effortful control with age, beta, and condition as predictors. I focused on the beta main effect, or interactions with the beta factor. Results show that brain activity in these regions was not predictive of effortful control at 42months.

#### 3.3.2.4 Overlapping neural systems across tasks

Attentional control and WM have overlapping neural correlates (Duncan & Owen, 2000; Munakata et al., 2011), particularly early in development (Astle & Scerif, 2009; Scherf et al., 2006; Shing et al., 2010; Velanova et al., 2008). However, an important question is whether the component abilities of working memory and attention rely on overlapping neural systems before the age of 4. Figure 3.38 shows the overlap across tasks. The left panel shows the overlap between UEA (shown in purple) and IOWA (shown in fuchsia). These tasks are thought to tap different systems of attention, executive and orienting attention respectively. Recall that these tasks were not related behaviorally (i.e., non-significant cross-task correlations). However, both tasks engaged l-DLPFC and l-TPJ. Importantly, these regions are part of the dorsal and ventral attention network. I further explored if individual differences in brain activity in these regions across tasks were correlated. Results show that activity in these regions was not correlated, $p > 0.1$, $n = 22$.

The right panel shows adjacent clusters from the IOWA and VWM (shown in dark blue) fNIRS results. Both tasks engaged r-IPS. This region has been previously associated with attention and working memory. Recall that behavior in the IOWA invalid no competition condition was negatively related to performance in the low working memory condition such that participants with better working memory in this load were less efficient in this IOWA condition (see figure 3.18). Changes in neural activity across tasks were not correlated, $p > 0.1$, $n = 19$.

## 3.4 Discussion

The goal of this study was to explore the development of EF subcomponents at two levels – brain and behavior – with en eye toward examining whether looking measures that index these component processes predict the development of executive control. I measured attentional control, visual working memory, effortful control and executive function in 30-month-old toddlers. Additionally, I measured executive function and collected parent-reported effortful control at 42-months. I will first discuss the behavioral results followed by the imaging results.

In the VWM domain, we saw that participants looking dynamics were modulated by load and age. Specifically, results showed that older participants preferred to look to the change side in all loads, while younger participants only showed a preference to look at the changing side on the lowest load. This is particularly interesting considering the small age range of the participants in this study. Note that the preferential looking task did not yield terribly clear load effects in study 1, particularly with the older age groups. Considered together with the present data, I conclude that this task is a sensitive measure of VWM capacity early in toddlerhood, but appears to become less effective as children increase in age.

In the attention domain, beginning with the IOWA task, we saw a nice replication of Chapter 2 in that performance was better in the no competition condition vs the competition condition. This also replicates Ross-Sheehy et al. (2015). Additionally, results show that an invalid cue resulted in worse performance when compared to a valid cue.

In the UEA task, we saw that within the subset of participants who learned the contingency between the attention getter and the subsequent location of the target, the probability to produce and anticipatory look was around 50%, which is consistent with results from participants in this same age range in Chapter 2. Further, participant's percent of anticipation in this study was lower than in previous work looking at percent anticipation in a visual sequence task from 24- to 36-months (Rothbart et al., 2004). In that study, the researchers reported that by 24 months, participants could anticipate the correct (ambiguous) location of a 1213 visual sequence (e.g., 60% of the time). A plausible explanation for the differences in findings across tasks is that, in the UEA task, trials that elicit anticipatory looks are foiled by test trials. In test trials, participants see the target item on both sides of the screen. Thus, if the participant did not have a strong representation of the relationship between the AG and the target location, this type of trial could disrupt their ability to anticipate.

The results from the disengagement condition suggest that there was a slight trend that participants became more efficient as they got older. Notably, these results replicate what we saw in Chapter 2. Moreover, these results suggest this task is among the most difficult -within the study- for the toddlers.

Moving on to the outcome measures, the results from both effortful control measures (Gift Wrap at 30mo and parent-reported effortful control at 42mo) were consistent with what we saw in the previous chapter. In particular, gift wrap peeking scores ranged from 2-3 on average, similar to age-matched counterparts in the previous chapter. Additionally, results from the parent-reported temperamental effortful control show a gender effect, in which girls have a higher score than boys. This is also consistent with results from Chapter 2. Importantly, this gender effect seems to be more noticeable as children get older. Similarly, the executive function results reported here are consistent with the previous chapter. Critically, with the addition of the 42mo results, we can see individual trajectories of EF from 30- to 42-months. Note that I was not able to obtain a full sample of 42-month-olds' MEFS data because collection of these data is on-going. Thus, I did not have a sufficient sample size to look at whether these individual trajectories were predicted by other neural or behavioural measures. This will be an important question to examine in future work.

In summary, I generally replicated the behavioral patterns observed in chapter 2. Next, I examined correlations across tasks. I found that high WM was negatively correlated with low WM/med WM and EC at 42 months. Detecting change in the high WM condition is unlikely at this age range given that previous results suggest that a memory load of 6 items exceeds the capacity of VWM (see Simmering, 2016); thus, the anti-correlation with lower loads is expected. In this context, the negative correlations suggest that children with better VWM abilities tend to have better EC at 42 months. Further, the low WM score was negatively correlated with BIS scores from the invalid IOWA condition. Recall that BIS is a measure of efficiency that integrates accuracy and RT. The negative correlation could reflect a speed of processing effect: participants who are fast visual information processors and good at detecting change in the VWM task may react too fast in the invalid IOWA condition producing a low BIS score.

In the previous chapter, I reported that anticipatory looking was predictive of concurrent effortful control. Based on this, I explored the relationship between 30-month old measures and effortful control at 42 months. Results indicate that efficiency of disengagement and the interaction between age and the probability to produce an anticipatory look in the UEA task at 30 months are predictors of effortful control at 42 months. This partially replicates and further extends the results from Chapter 2. Interestingly, while Rothbart et al. (2004) reported that by 24 months participants were quite good at anticipating a visual sequence, this ability was not related to EC in children aged 24-36mo. Perhaps the greater difficulty of the task helped reveal important individual differences.

In contrast to Geeraerts et al. (2019), Wass and Smith (2014), Holmboe et al. (2018), and the results form Chapter 2, I found a relationship between attentional disengagement and executive control in the present study. Attentional disengagement has been related to the orienting network, as children in the UEA task must overcome an exogenous visual cue. Posner and colleagues have hypothesized that early in development (<4 years), self regulation is exerted by the orienting attention network and this shifts over development such that executive attention takes over. Considering my results in light of the Posner et al. (2014) hypothesis, my results suggest that at 30 months, both networks, namely the orienting and executive attentional networks, play an important role in predicting later effortful control. Thus, toddlers may be in a transitioning period in which they rely on both systems to regulate their cognition and behavior. Critically, these measures were not correlated with each other, thus at some level, they are indexing different attentional processes. This provides an interesting framework for thinking about the imaging results.

### 3.4.1 Neural bases of executive function subcomponents

**3.4.1.0.1 VWM** The VWM results show robust engagement of brain regions involved in the previously identified VWM network (Delgado Reyes et al., in rev; Buss et al., 2014; Bunge & Wright, 2007; Edin, Macoveanu, Olesen, Tegnér, & Klingberg, 2007; Fair et al., 2007; Wager & Smith, 2003; Owen et al., 2005; Rottschy et al., 2012). There was task-related activity in bilateral frontal, right parietal, and left occipital cortex. Importantly, activity in r-IFG, r-IPS and l-VOC was modulated by load and age. Consistent with previous work, these results showed task-specific activation in bilateral portions of the frontal cortex, namely r-IFG and l-MFG (Delgado Reyes et al., in rev; Buss et al., 2014). Moreover, my investigation into the relationship between neural activity and behavioral performance in the task revealed that activity in l-VOC is predicted by participant's performance in the task. Results revealed differential activation in l-VOC, a site for color representation, suggesting a link between increased neural activity, changes in the representation of colors, and enhanced performance in the task. This relationship was mediated by the number of items present in the display. Even though I found task-relevant activity in the frontal cortex (e.g., IFG), the relationship between activity in l-VOC and behavior is consistent with previous work suggesting that VWM performance is primarily driven by the posterior cortex early in development (Scherf et al., 2006).

Activation in IFG was related to effortful control such that younger children who showed higher IFG activation had higher effortful control. Recall that for both younger and older children, IFG is supporting performance for within-capacity loads in the WM task (see Edin et al., 2009). It is possible that younger children who recruit more frontal cortex involvement in VWM functions show better WM abilities earlier in development which promotes the emergence of greater effortful control.

**3.4.1.0.2 IOWA** The IOWA task elicited widespread cortical activation across the frontal, temporal, parietal and occipital cortices. Results showed task-related activity in DLPFC, TPJ, aIPS, MFG, IPS, and close to VOC. Importantly, this activity was modulated by task demands and is consistent with previously identified attentional networks (Vossel, Weidner, Driver, Friston,

& Fink, 2012).

Critically, my investigation of relationships with behavior revealed that DLPFC plays a role in supporting performance in the hard conditions in this task (e.g., control). DLPFC is part of the dorsal attention network and previous work has shown that this region is involved in the directing of attention to spatial locations (Corbetta, Miezin, Shulman, & Petersen, 1993; Nobre et al., 1997; Nobre, Gitelman, Dias, & Mesulam, 2000).

Further, results show that aIPS plays a particular role in supporting performance in the task. Children who have trouble completing this task, engage this region to support better performance. However, they do not engage this region in other, more difficult, conditions. For children who show good performance in the task, engagement of this region is higher on the harder conditions. It seems that worse performers are depleting all their resources in trying to perform in the easy conditions so once the harder conditions come up, they perform poorly. Critically, aIPS is also part of the dorsal attention network, which has been shown to be engaged in visuospatial cueing tasks (e.g., Corbetta, Kincade, Ollinger, McAvoy, & Shulman, 2000). Furthermore, previous research has reported that this network is involved in the selection of appropriate responses or actions necessary for orienting attention (Caspers et al., 2013). Thus, the patterns of activity see across conditions may be supporting the selection or planning of the rapid occulomotor response necessary to perform well in the task.

Importantly, activity within this dorsal attention network in task-relevant ways was predictive of individual differences in effortful control at 42 months, which is consistent with Posner et al. (2014). Specifically, results suggest that older children who activate TPJ in the invalid competitive condition (the hardest condition) have better EC at 42mo. In all, my results highlight how a distributed network controls attention in this task. Notably, there were robust individual differences localized on DLPFC and IPS, while DLPFC and TPJ activation was predictive of EC at 42mo. These neural data are particularly interesting given that IOWA task performance was not strongly related to performance of the other tasks with the exception of VWM in the low load condition, nor was performance in the IOWA task related to EF or EC outcome measures in either study.

**3.4.1.0.3 UEA** The UEA task elicited activity in fronto-temporo-parietal regions of the brain. In the anticipatory looking trials, there was an increase in brain activity in the frontal cortex over development. Interestingly, the contrast examining neural activity in trials where participants produced anticipatory looks vs when they didn't resulted in an inverse hemodynamic response in STG. Neural activity in this region was not related to individual differences in behavior. IFG showed an increase in neural activity related to anticipatory looking over development. In terms of disengagement, results showed neural activity in a left-lateralized frontal parietal network. Namely, activity was localized to M/SFG and TPJ. M/SFG showed an increase in disengagement over development. Critically, these regions are also involved in the dorsal attention network, and children with higher BIS scores showed greater TPJ activity. Despite robust relationships between behavioral performance in this task and effortful control at 42 months, brain activity was not predictive of effortful control.

**3.4.1.0.4 Overlapping neural systems across tasks** In the present study, measures of orienting attention and WM engaged rIPS. In the WM task, young children engaged IPS in the high load condition. IPS has been shown to be involved in VWM (e.g., Pessoa, Gutierrez, Bandettini, & Ungerleider, 2002;

Todd & Marois, 2004, 2005; Xu & Chun, 2006) but it has also been shown to play a role in visual attention (Bressler, Tang, Sylvester, Shulman, & Corbetta, 2008; Corbetta & Shulman, 2002). Thus these results are consistent with previous work reporting overlapping neural systems in supporting these cognitive functions.

Further, there was overlapping brain activity in DLPFC and TPJ for both attention tasks. Critically, within the UEA task, these regions were involved in disengagement, which has some overlapping task demands with IOWA conditions (e.g., control competition condition). In both tasks there was increased TPJ activation over development such that older children show increased activation in TPJ. Critically, within the UEA task, this activation pattern was related to participants' behavior such that better disengagement was predictive of higher activation within this region. In IOWA, this activation pattern was not related to individual differences in behavior but it was predictive of EC at 42 months. Thus, TPJ is involved in both tasks. Moreover, behaviorally, attentional disengagement in UEA is predictive of EC at 42 months. These results suggest that there are overlapping neural correlates across these two similar tasks. Critically, at the level of the brain, activity in TPJ in response to task demands might be an important index for elucidating relationships between attention and later EC. In line with previous research, out results are consistent with the idea that attentional disengagement requires involvement of prefrontal and parietal areas to support behavioral performance (Csibra, Johnson, & Tucker, 1997; Csibra, Tucker, & Johnson, 1998).

## 3.5 Conclusion

In summary, the present study replicated the results from the previous chapter in that I found that attentional control is related to executive control in toddlers and young children. Further, results from the present study provide evidence that measures of basic visual dynamics relate to longitudinal changes in cognitive development and executive control. Critically, and consistent with previous research, results showed task-relevant brain activity among WM and attention tasks in previously identified WM and attentional networks. Importantly, there was overlap in the spatial localization of these activation patterns which is consistent with the idea that WM and attention share neural correlates early in development. Importantly, the activation patterns reported here are predictive of later executive control and may serve as an index for later development.

The next step is to move this work to infancy to elucidate if the relationships reported here are present within the first year of life. In conjunction with the previous chapter, these results set the stage for future work to measure looking dynamics in infancy in order to predict longer-term executive control outcomes. Further, this work furthers our understanding of how changes in brain function lead to different developmental cascades from 30- to 42- months. I expand upon these themes in the General Discussion.

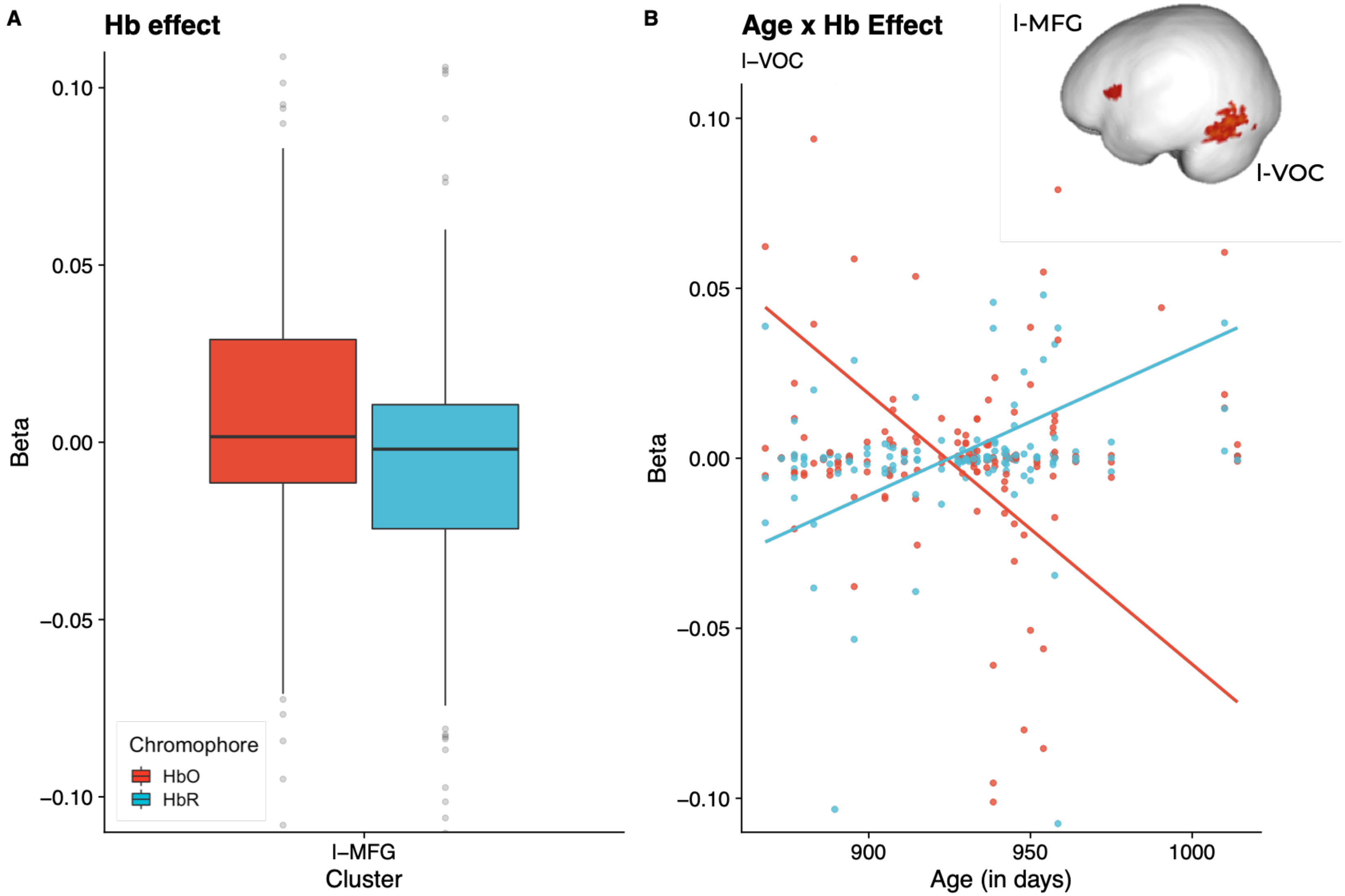

Figure 3.20: fNIRS ANOVA results for the VWM task. Panels show brain activity in each cluster as a function of (A) Hb, (B) Age x Hb. Brain image shows significant clusters from the fNIRS ANOVA after familywise correction.

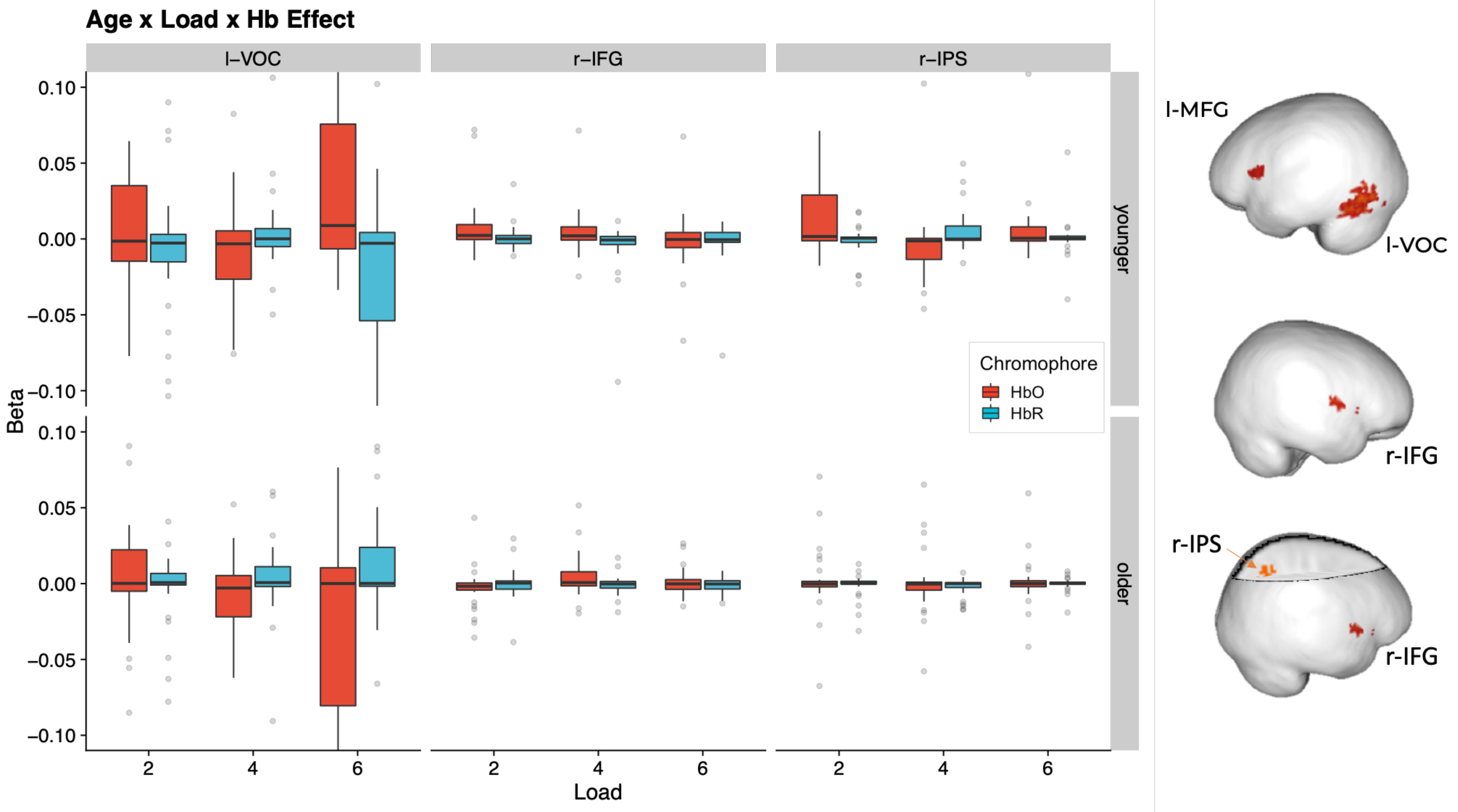

Figure 3.21: fNIRS ANOVA results for the VWM task. Panels show brain activity in each cluster as a function of (A) Age x Load x Hb. Brain images on the right show significant clusters from the fNIRS ANOVA after familywise correction. Age in days was median split to facilitate visualization.

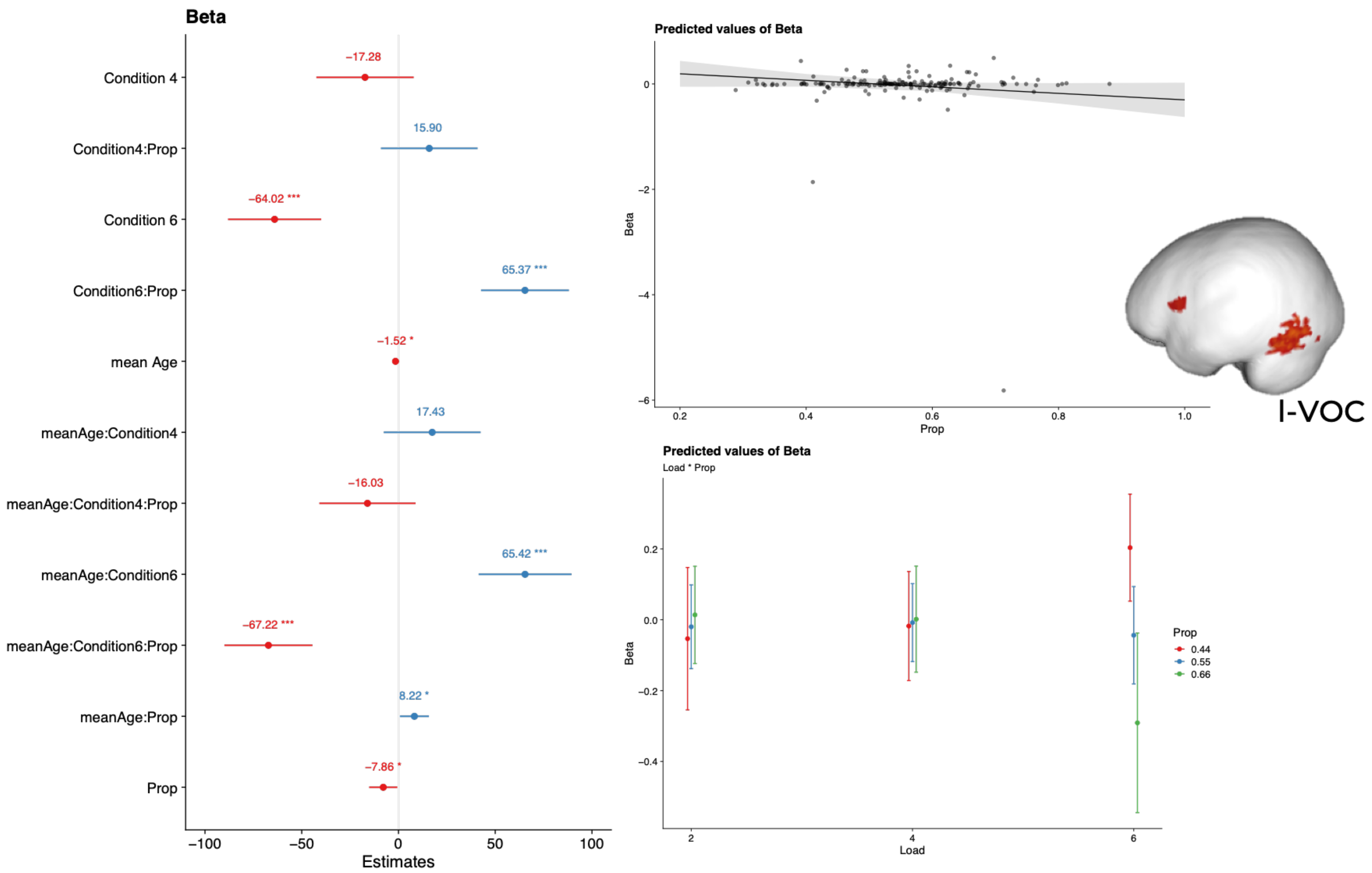

Figure 3.22: Brain x Behavior relationships in VWM task. Figure shows results from a model predicting neural activity in VOC with behavior. Panel A shows a forest plot with the standardized model estimates with confidence intervals. Panel B shows the main effect of proportion looking to changing side. Panel C shows the interaction between proportion looking to the changing side and load.

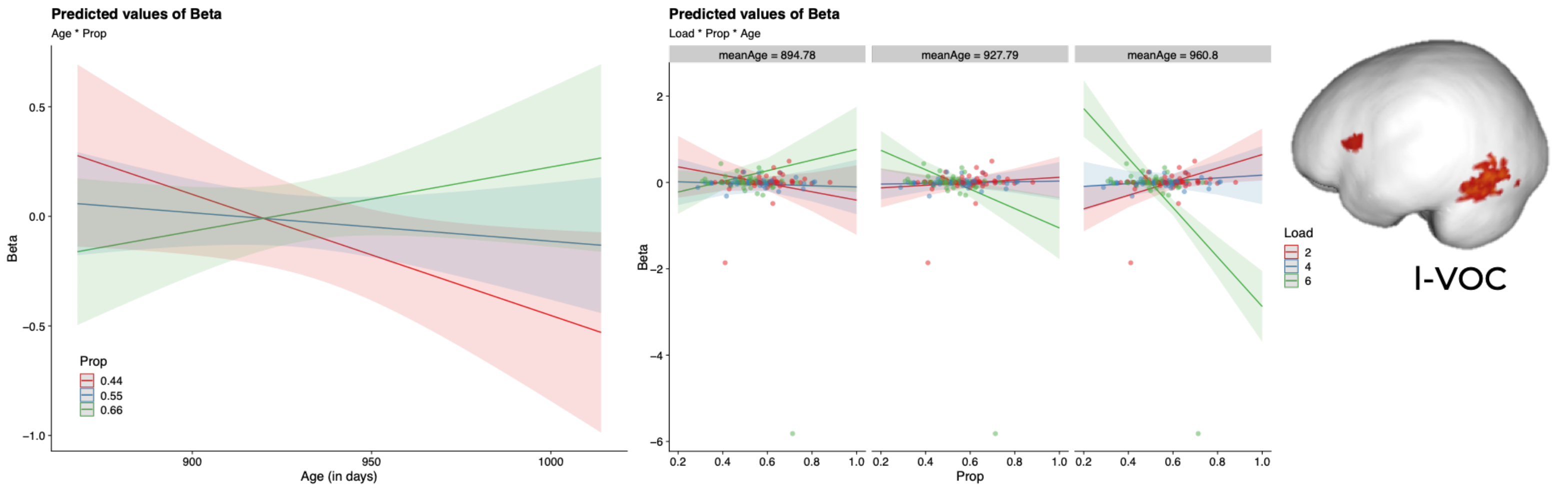

Figure 3.23: Brain x Behavior relationships in VWM task. Figure shows results from a model predicting neural activity in VOC with behavior. Panel A shows the interaction between age and proportion looking to the changing side. Panel B shows the interaction between age and proportion looking to the changing side and load. Age in days was grouped into low, medium, high to facilitate visualization.

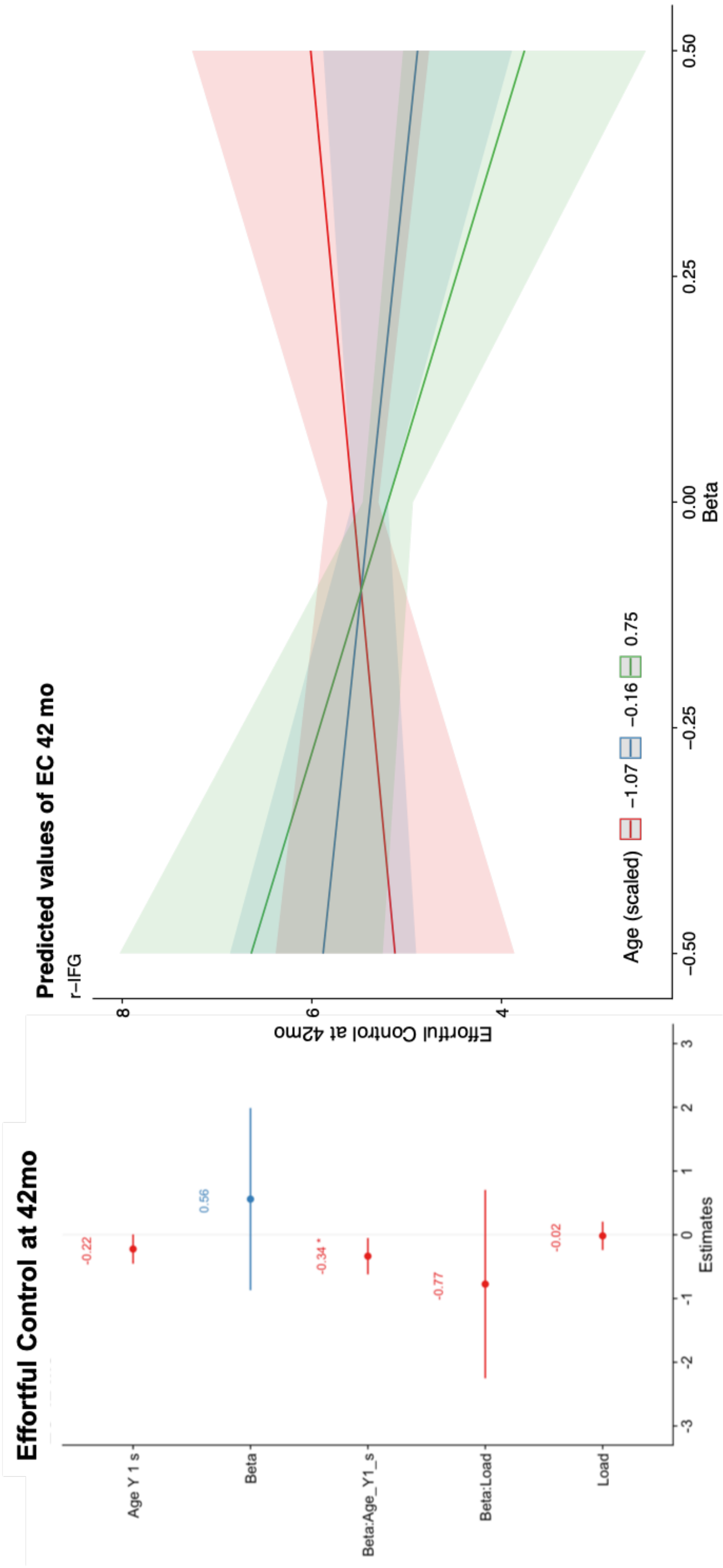

Figure 3.24: Predicting effortful control with brain activity in rIFG during the VWM task. The left panel shows a forest plot showing the standardized model coefficients and confidence intervals. The right panel depicts the interaction between age and neural activity in IFG. Age in days was grouped into low, medium, high to facilitate visualization.

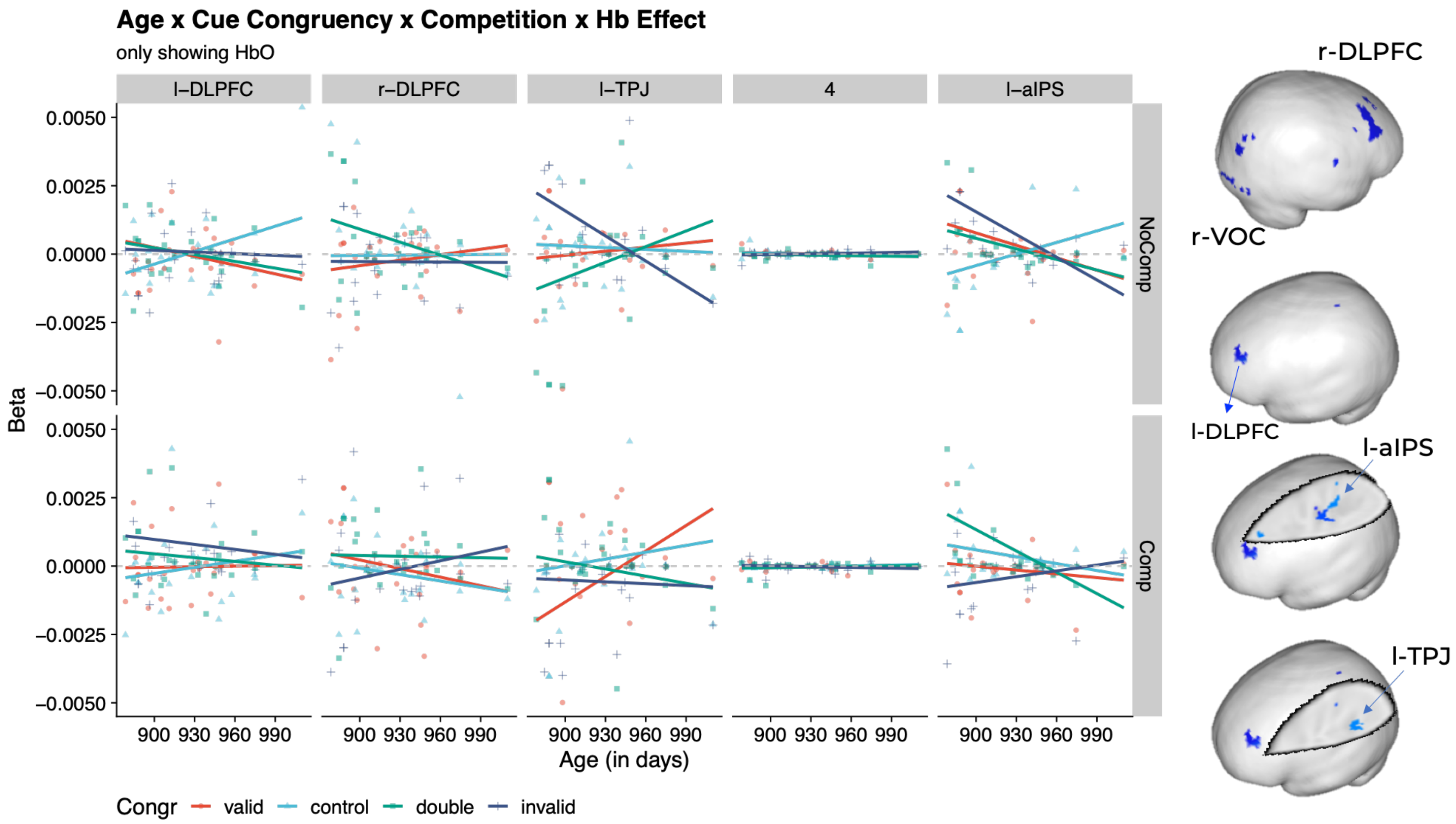

Figure 3.25: fNIRS ANOVA results for the IOWA task. Brain images on the right hand side show significant clusters from the fNIRS ANOVA after familywise correction. The panel of the left shows brain activity in each cluster as a function of the interaction between Age x Cue Congruency x Competition x Hb.

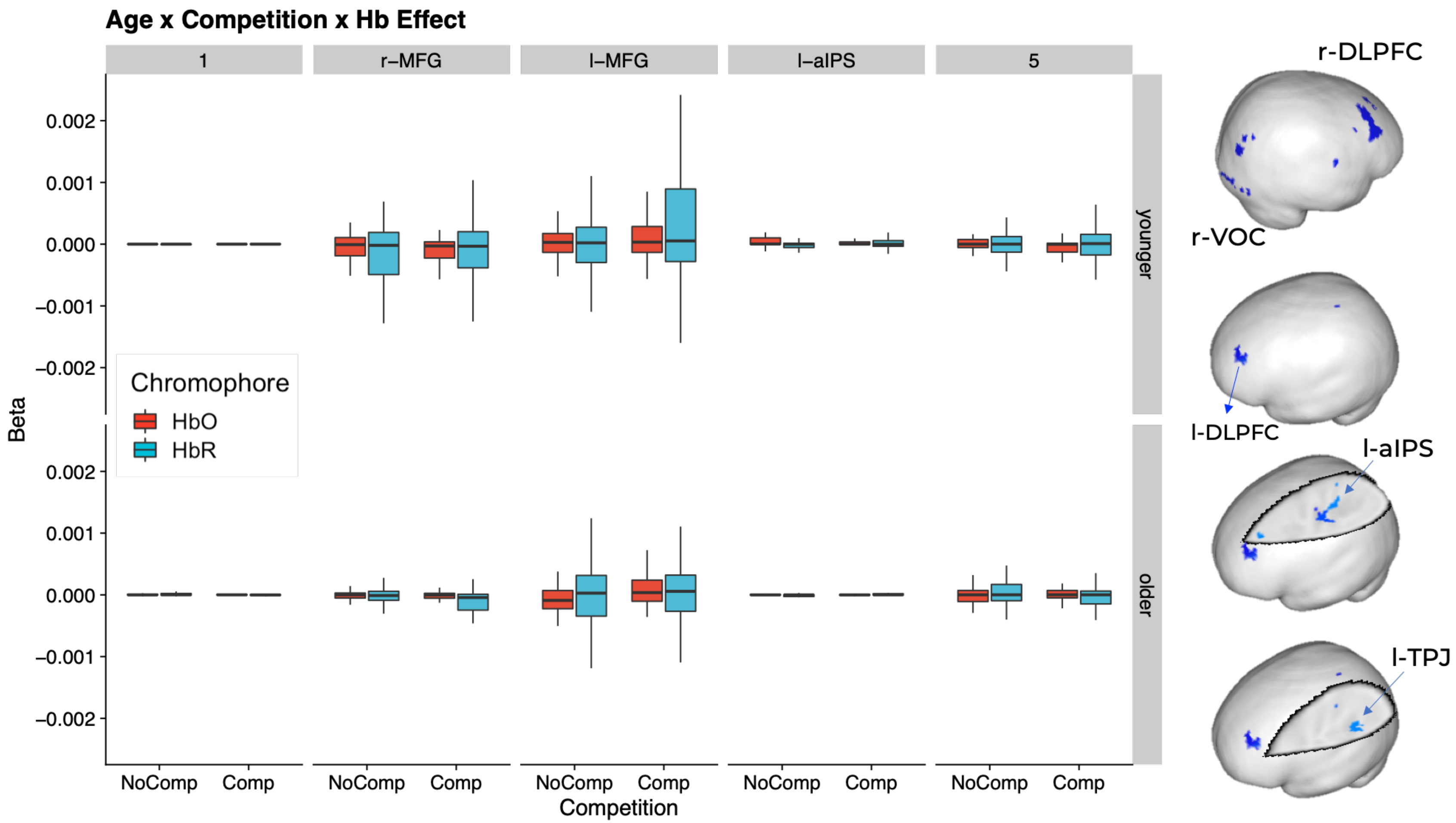

Figure 3.26: fNIRS ANOVA results for the IOWA task. Brain images on the right hand side show significant clusters from the fNIRS ANOVA after familywise correction. The panel of the left shows brain activity in each cluster as a function of the interaction between Age x Competition x Hb. Age in days was median split to facilitate visualization.

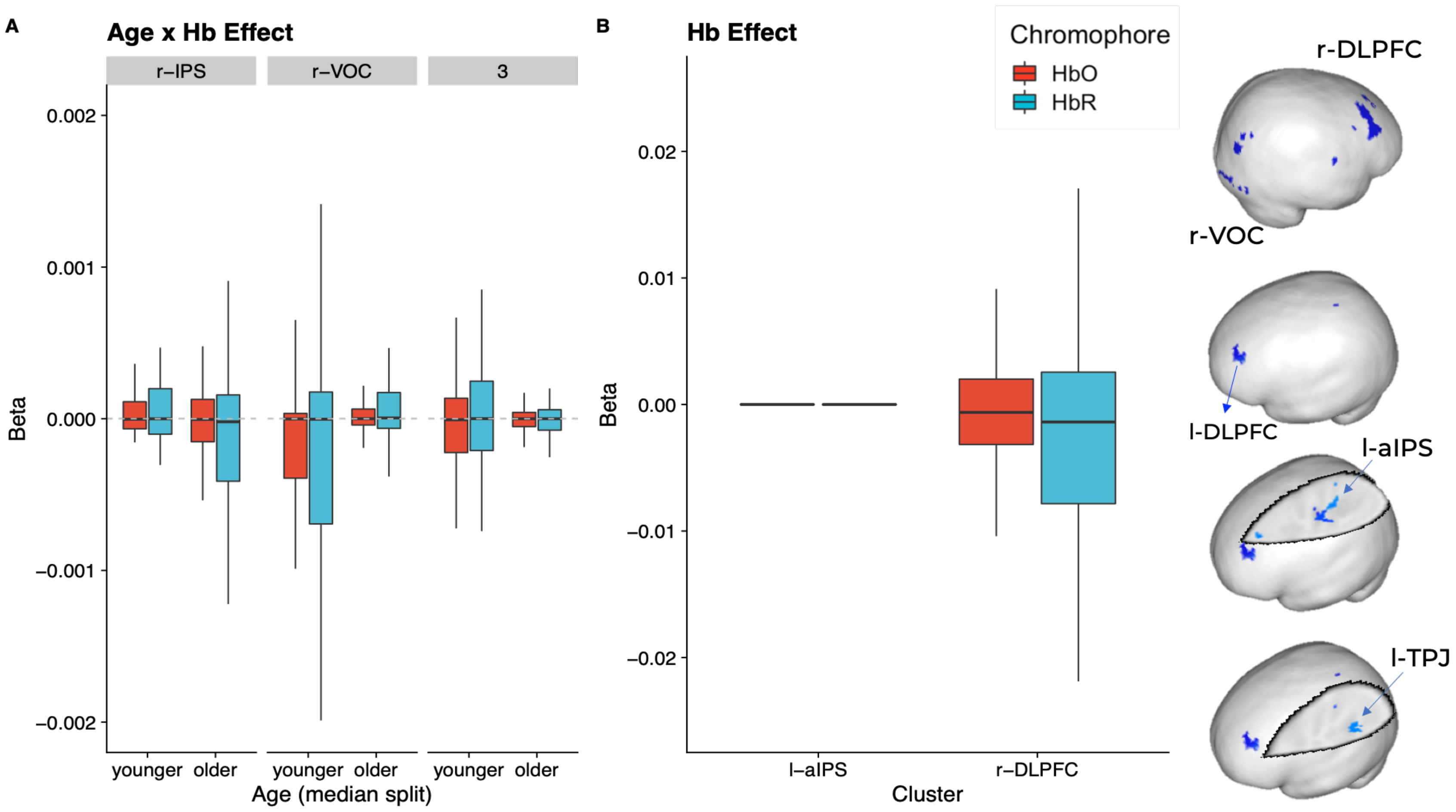

Figure 3.27: fNIRS ANOVA results for the IOWA task. Brain images on the right hand side show significant clusters from the fNIRS ANOVA after familywise correction. The panel of the left shows brain activity in each cluster as a function of the interaction between Age x Hb (Panel A) and Hb (Panel B). Age in days was median split to facilitate visualization.

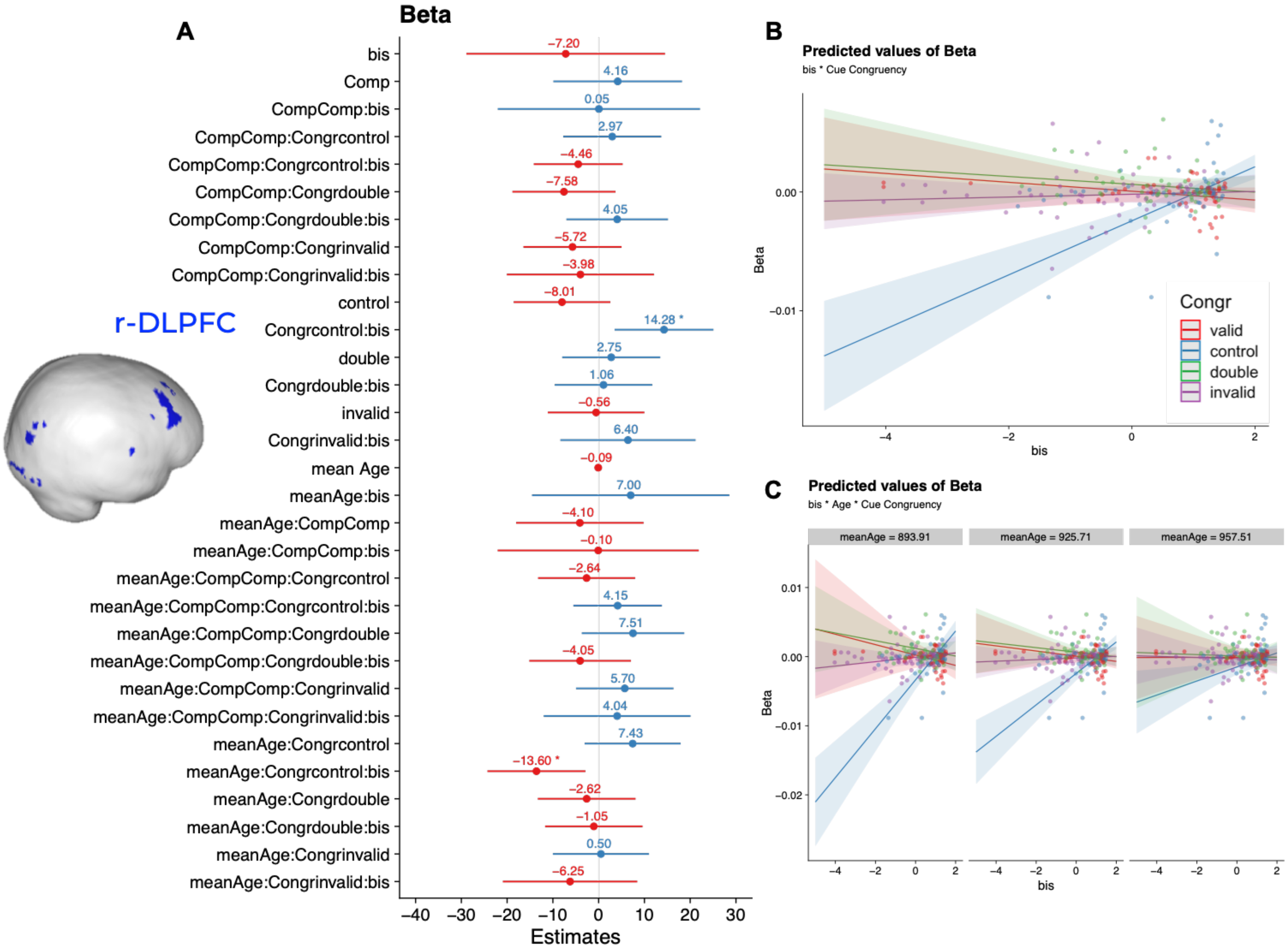

Figure 3.28: Brain x Behavior relationships in the IOWA task. Figure shows results from a model predicting neural activity in r-DLPFC with behavior. Panel A shows a forest plot with the standardized model estimates with confidence intervals. Panel B shows the interaction between BIS X Cue Congruency. Panel C shows the interaction between BIS x Competition x Cue Congruency. Panel D shows the interaction between BIS x Age x Cue Congruency. Age in days was grouped into low, medium, high to facilitate visualization.

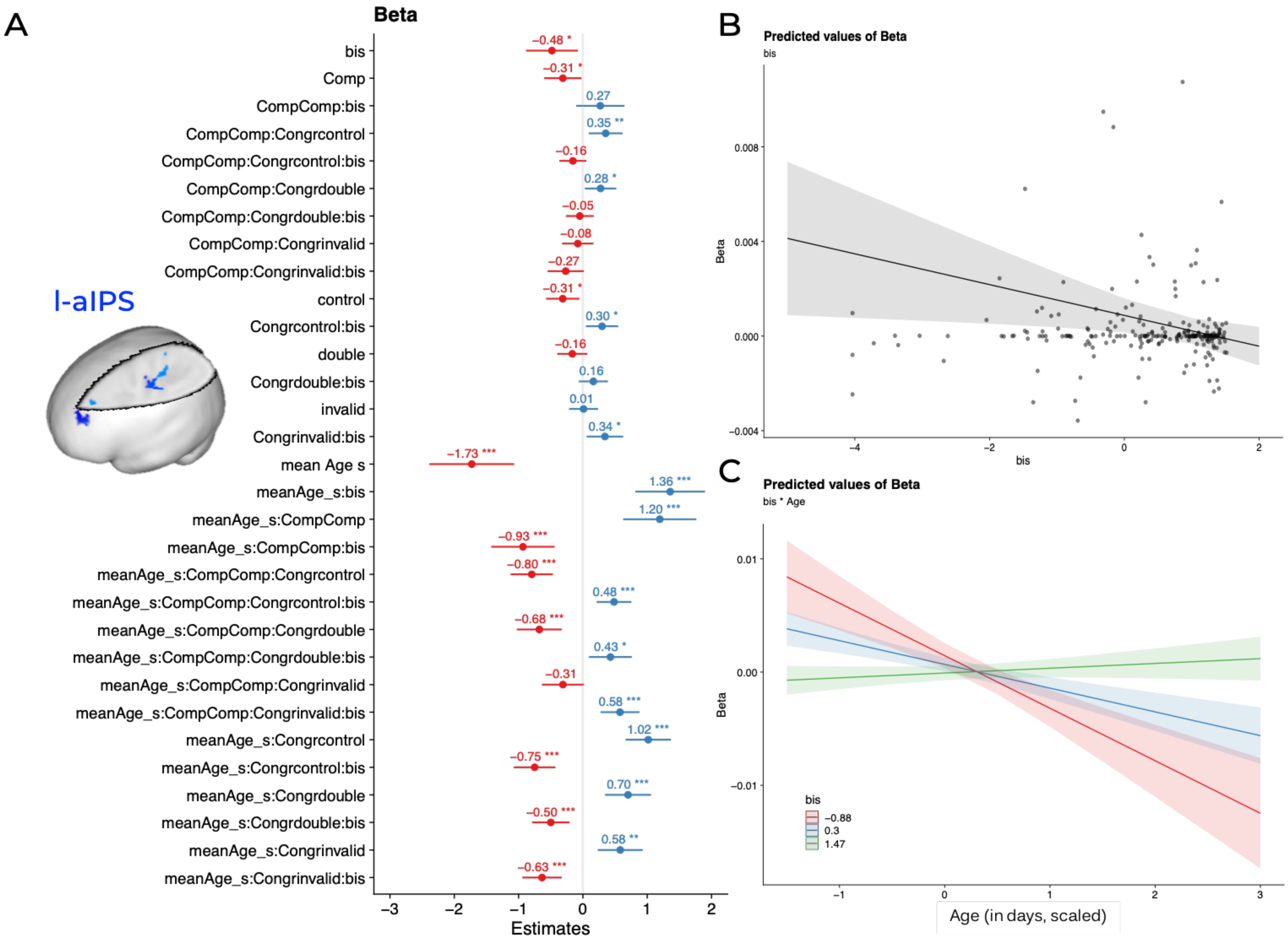

Figure 3.29: Brain x Behavior relationships in the IOWA task. Model predicted neural activity in l-aIPS as a function of behavior. Panel A shows a forest plot with the standardized model estimates with confidence intervals. Panel B shows the main effect of BIS. Panel C shows the interaction between BIS x Age.

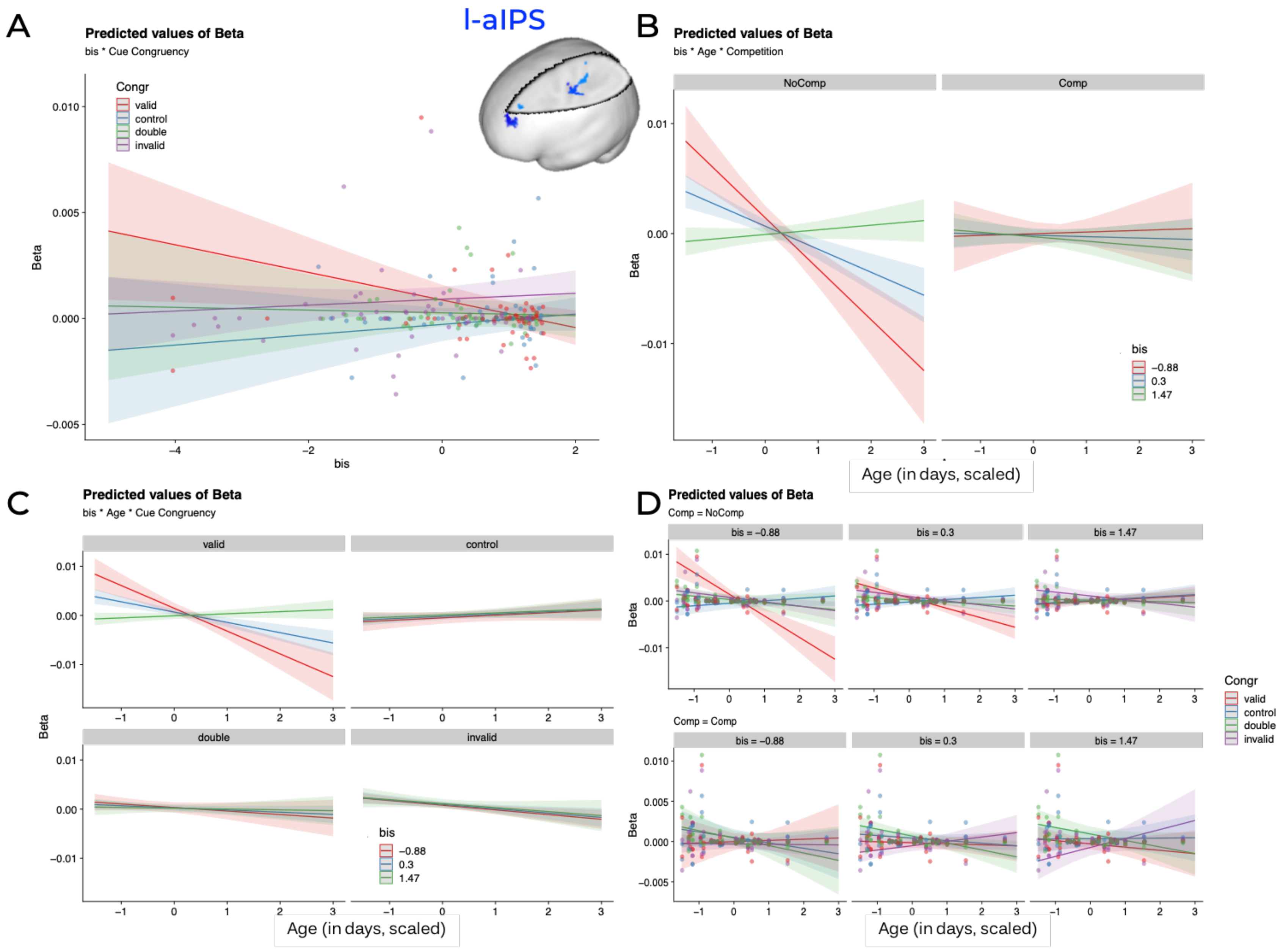

Figure 3.30: Brain x Behavior relationships in the IOWA task. Model predicted neural activity in l-aIPS as a function of behavior. Panel A shows the interaction between BIS X Cue Congruency. Panel B shows the BIS x Age x Competition. Panel C shows the interaction between BIS x Age x Cue Congruency. Panel D shows the interaction between BIS x Age x Cue Congruency x Competition.

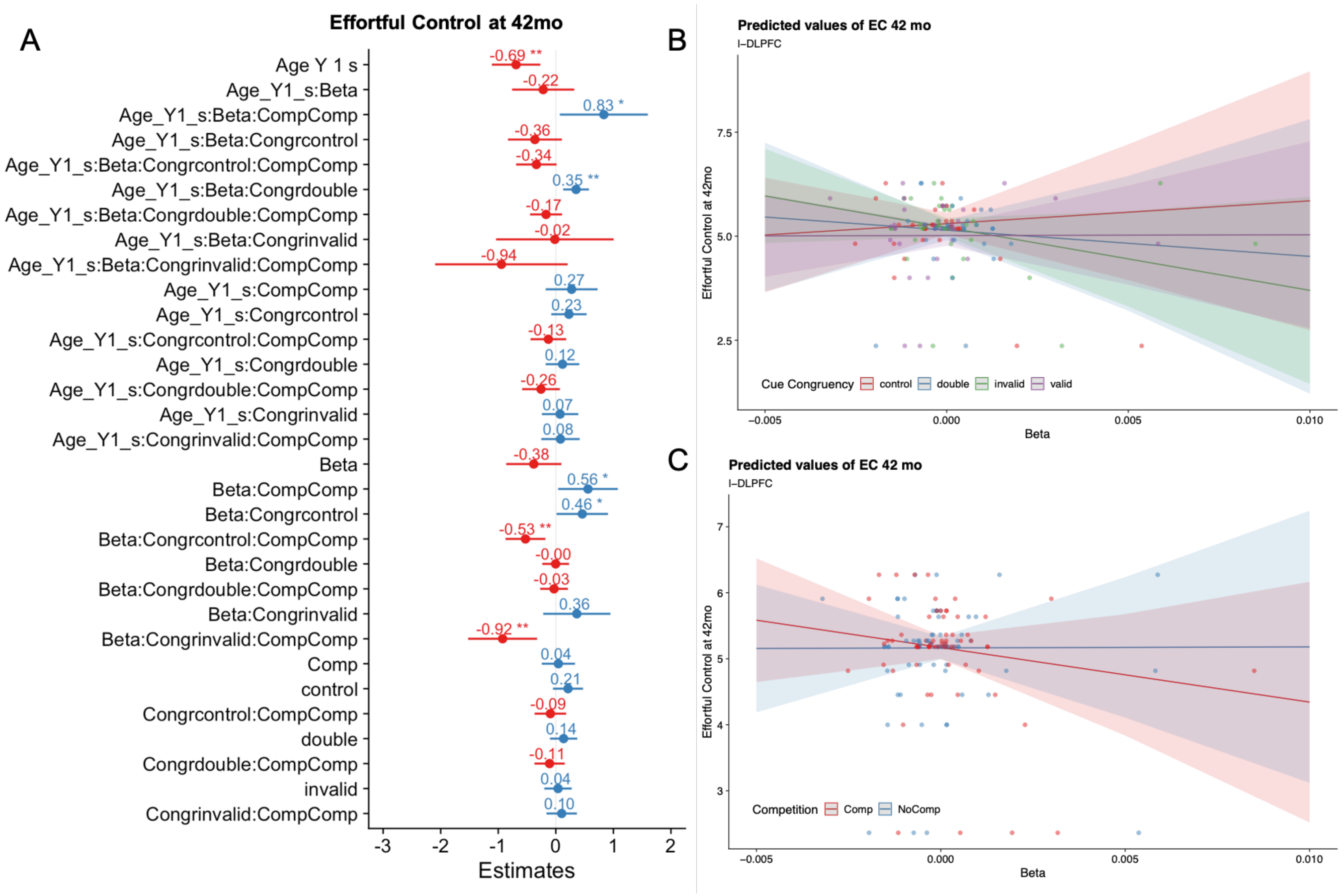

Figure 3.31: Predicting effortful control with brain activity in l-DLPFC during IOWA task. Panel A shows a forest plot showing the standardized model coefficients and confidence intervals. Panel B depicts the interaction between cue congruency and neural activity in DLPFC. Panel B depicts the interaction between competition and neural activity in DLPFC.

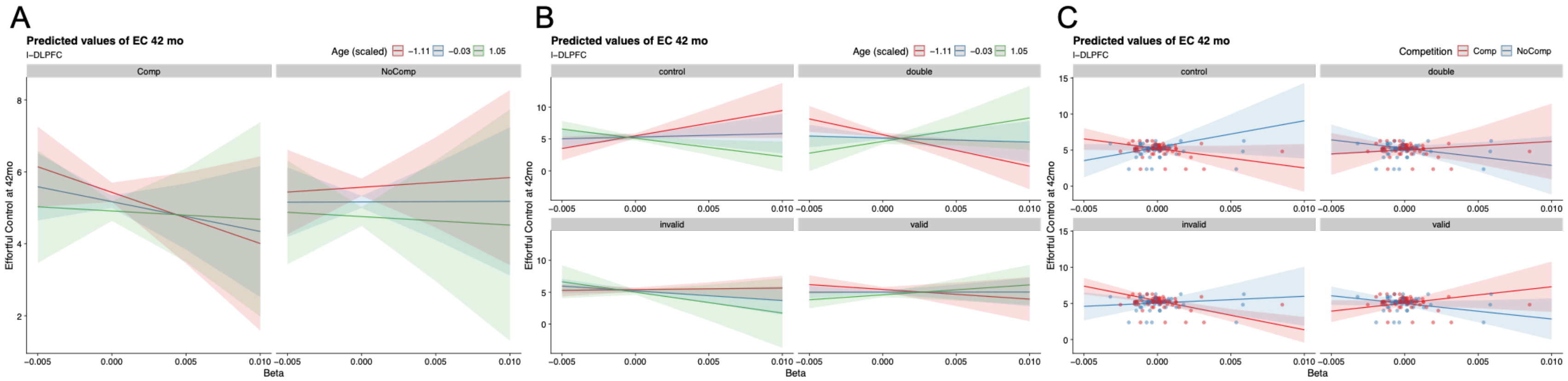

Figure 3.32: Predicting effortful control with brain activity in l-DLPFC during IOWA task. Panel A depicts the interaction between age and neural activity in DLPFC. Panel B depicts the interaction between age, cue congruency and neural activity in DLPFC. Panel C depicts the interaction between competition, cue congruency and neural activity in DLPFC. Age in days was grouped into low, medium, high to facilitate visualization.

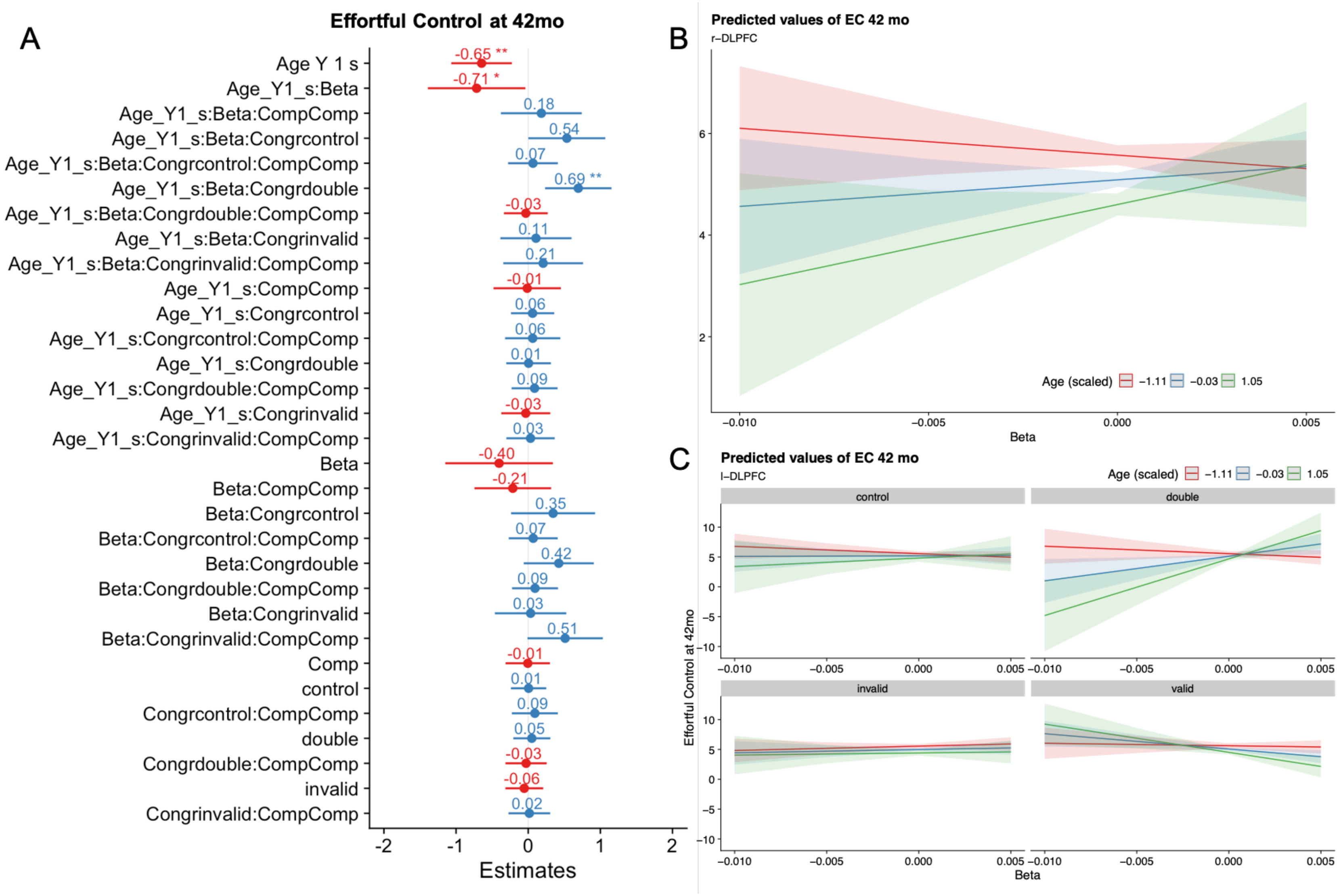

Figure 3.33: Predicting effortful control with brain activity in r-DLPFC during IOWA task. Panel A shows a forest plot showing the standardized model coefficients and confidence intervals. Panel B depicts the interaction between age and neural activity in DLPFC. Panel C depicts the interaction between age, cue congruency and neural activity in DLPFC. Age in days was grouped into low, medium, high to facilitate visualization.

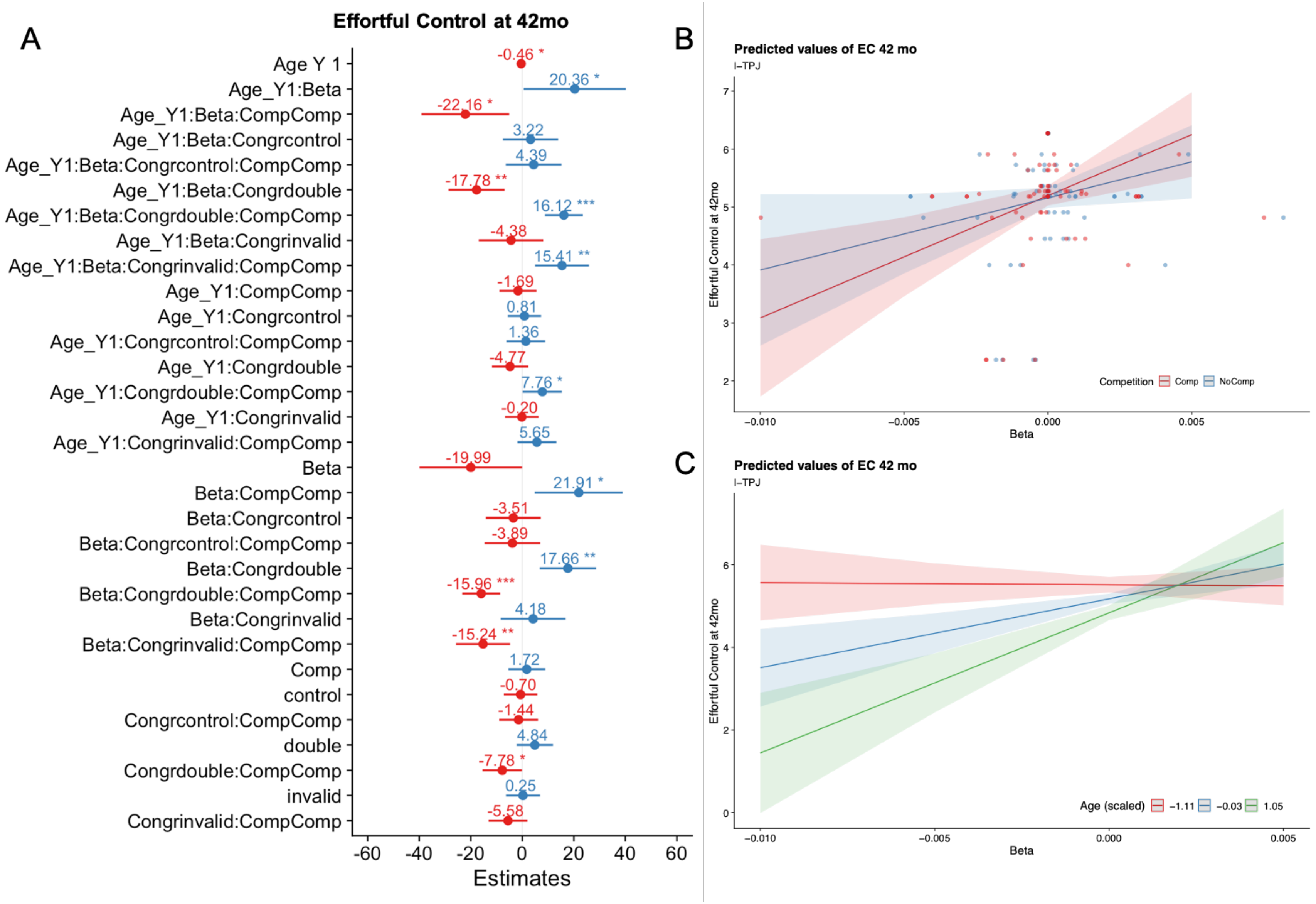

Figure 3.34: Predicting effortful control with brain activity in l-TPJ during IOWA task. Panel A shows a forest plot showing the standardized model coefficients and confidence intervals. Panel B depicts the interaction between competition and neural activity in TPJ. Panel C depicts the interaction between age and neural activity in TPJ. Age in days was grouped into low, medium, high to facilitate visualization.

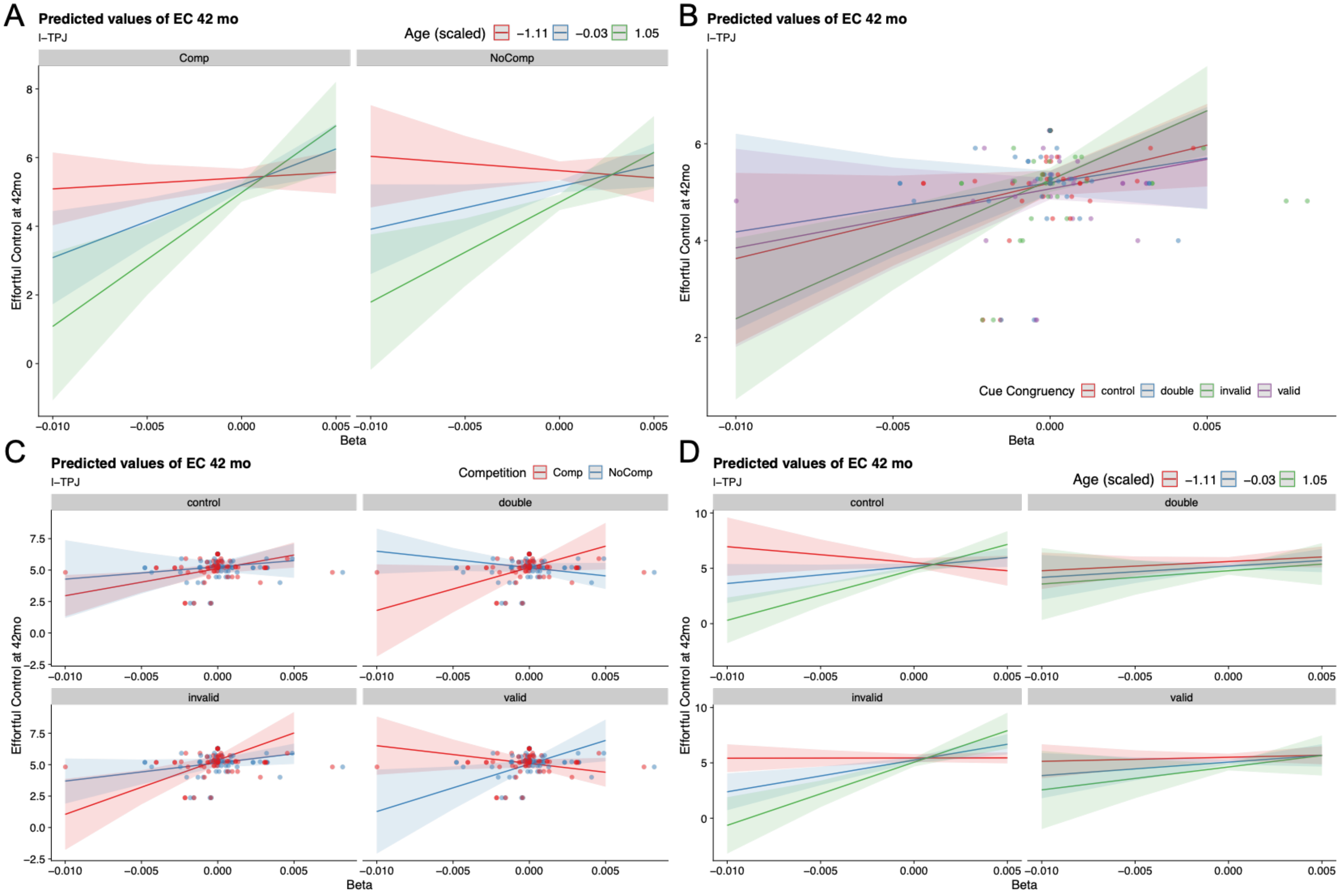

Figure 3.35: Predicting effortful control with brain activity in l-TPJ during IOWA task. Panel A depicts the interaction between age, competition and neural activity in TPJ. Panel B depicts the interaction between cue congruency and neural activity in TPJ. Panel C depicts the interaction between competition, cue congruency and neural activity in TPJ. Panel D depicts the interaction between age, cue congruency and neural activity in TPJ. Age in days was grouped into low, medium, high to facilitate visualization.

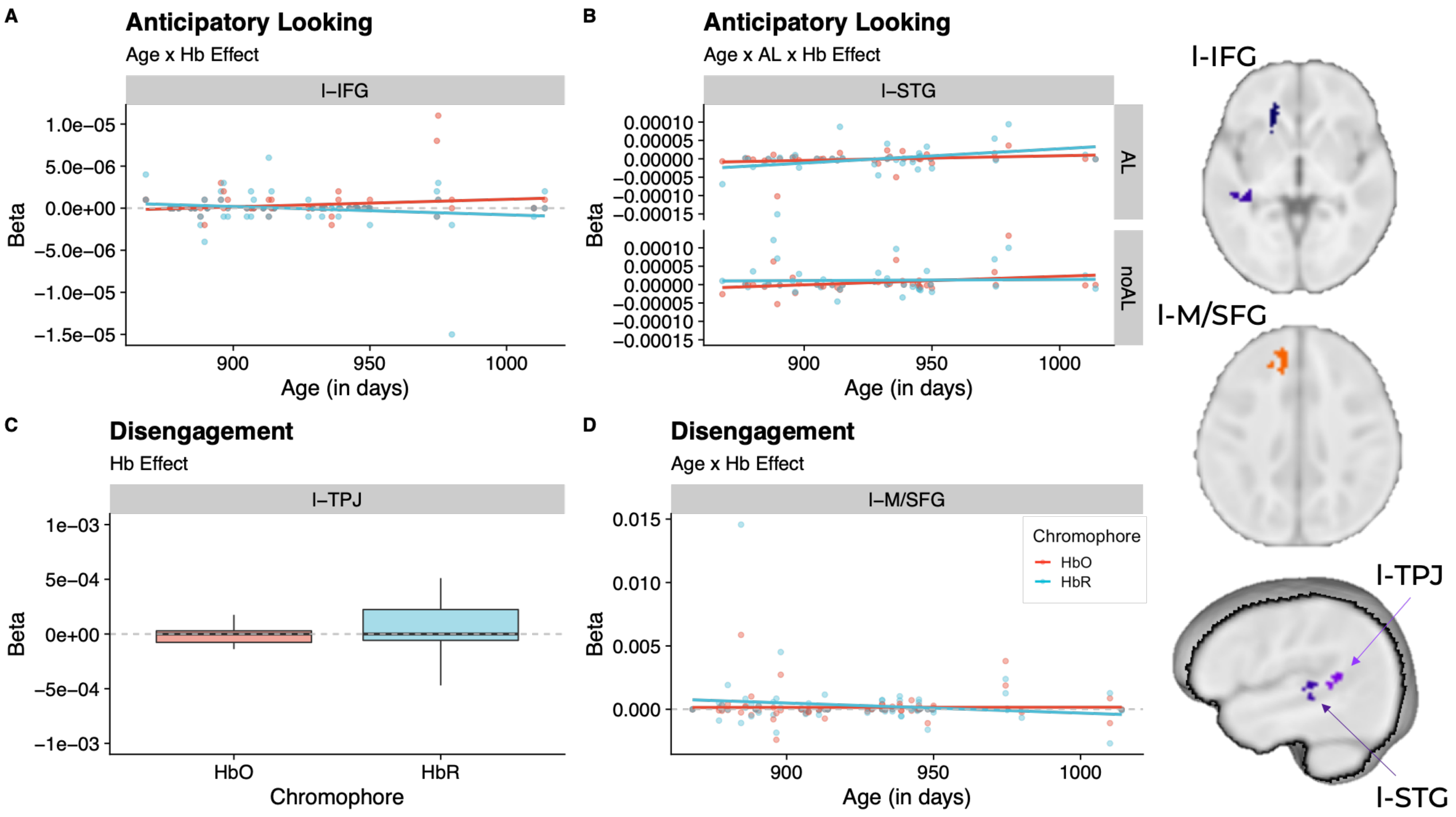

Figure 3.36: Combined fNIRS ANOVA results for the UEA task. Brain images on the right hand side show significant clusters from the fNIRS ANOVA after familywise correction. Panels A and B show results for the Anticipatory Looking ANOVA. Panel A shows brain activity in each cluster as a function of Age x Hb and panel B shows brain activity as a function of Age x AL x Hb. Panels C and D show results for the Disengagement ANOVA. Panel C shows brain activity as a function of Hb and panel D shows brain activity as a function of Age x Hb. red = HbO, blue = HbR

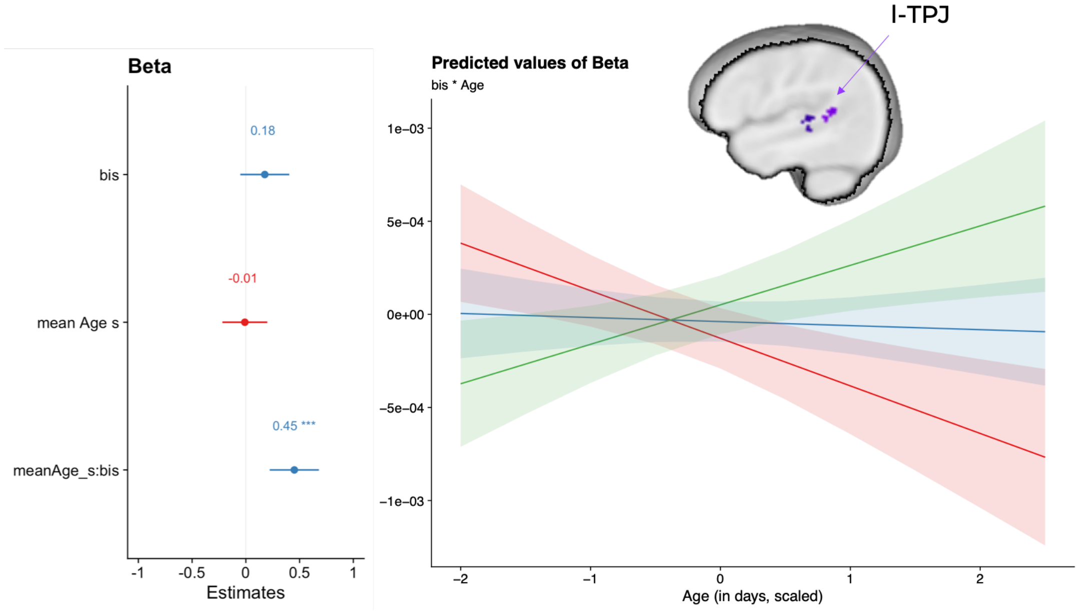

Figure 3.37: Brain x Behavior relationships in the UEA task. Figure shows results from a model predicting neural activity in l-TPJ with behavior. Panel A shows a forest plot with the standardized model estimates with confidence intervals. Panel B shows the interaction between BIS x Age.

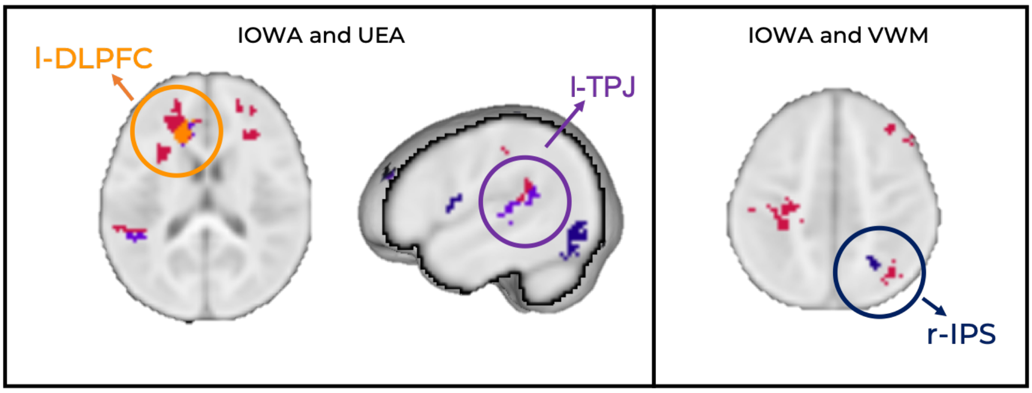

Figure 3.38: Overlapping neural systems across tasks.The left panel shows overlap across IOWA and UEA tasks and the right panel shows IOWA and VWM-PL tasks. colors: fuchsia = IOWA, purple = UEA, dark blue = VWM-PL, orange = overlap between IOWA and UEA.

# Chapter 4

# General Discussion

In recent years, there has been a growing interest in exploring how executive functions develop in the first three years of life (for reviews, see Hendry et al., 2016; Fiske & Holmboe, 2019). The main goal of this project was add to this literature by investigating if measures of visual dynamics within the attention and working memory domains are predictive of concurrent and later developing executive control. In particular I explored how rudimentary forms of attention and WM interact and co-develop to support developing executive control skills.

First, I asked if looking measures of attention and WM are predictive of executive control in a sample of 2 to 6-year-old children. Overall, results showed age-related changes across all domains, with expected increases in cognitive skill and complexity as children increased in age. Critically, results suggest that some of these measures are indeed predictive of concurrent effortful control but are not related to other measures of executive function. In particular, consistent with what has been reported in the literature regrading the role of the executive attention network in self regulation (Posner et al., 2014), I found that executive attention, in the form of anticipatory looking, was predictive of effortful control. Moreover, my results suggest a link between anticipatory looking and WM such that when children are confronted with high WM demands, attention supports behavioral performance. Thus, we have evidence that measures of basic visual dynamics relate to aspects of cognitive development and executive control.

Previous work investigating the development of executive function in children has put forward two conflicting accounts about the structure of EF in early development. On one hand, EF has been conceptualized as a set of interrelated but functionally distinct components. On the other hand, some researchers have reported that EF loads onto a single common factor. However, many of these studies rely on observations within narrow age ranges, for instance, the toddler or preschool period, but not across them. Consequently, it is hard to make inferences about developmental cascades based on these data. My study moves beyond this prior work in that I had participants as young as 24- and as old as 72- months. Looking across the two studies, I can speculate about emerging differentiation across development. In particular, we saw relationships between attention working memory and EC across the full age range. Critically, these relationships were more distributed early in development, where we saw relationships between orienting attention, executive attention, working memory and EC. This could indicate that an initially distributed system earlier in development becomes more functionally distinct later in development. Importantly, the relationship we observed across EC and attentional control is consistent with Tiego et al. (2019)'s report that executive attention is the common cognitive mechanism that underlies behavioral and cognitive control, as indexed by measures of EF and EC.

I then asked what are the mechanisms underlying these visual dynamic processes and whether they are predictive of executive function and control.

To investigate these mechanisms, I used fNIRS to investigate working memory and attention in 30 month-old toddlers. Results suggest that both WM and attention are predictive of developing executive control at different levels across tasks. At the level of the brain, all three tasks activate canonical parts of the frontoparietal network involved in VWM and the dorsal attention network involved in attention tasks. Critically, results indicate that there are key brain regions (e.g., IFG, IPS, TPJ) within these networks that are predictive of later effortful control.

For instance, the WM results suggest that brain activity in canonical WM regions is modulated by age and load. Importantly, performance in this task was primarily driven by posterior cortex. However, frontal regions lent support in within-capacity loads (Edin et al., 2009) and neural activity in this region was predictive of EC at 42 months.

In the attention domain, the UEA task elicited brain activity in fronto-temporo-parietal regions. Notably, disengagement trials elicited activity in a left-lateralized frontoparietal network that included M/SFG and TPJ. Despite robust relationships between behavioral performance and neural activity in TPJ, and relationships between attentional disengagement and later effortful control, brain activity in TPJ from this task was not predictive of effortful control at 42 months.

These results are interesting when considered in light of results from the IOWA task. This task elicited neural activity in regions of the dorsal attention network. Critically, the investigation of relationships with behavior revealed that DLPFC plays a critical role in supporting performance in the hard conditions in this task (e.g., control). Further, results suggest that activity in aIPS scales with task difficulty in a way that depends on the skills of the individual child. That is, activity in this region seems to be indicative of which conditions the brain is working hard in to support performance. Children who had low BIS scores, tended to have greater aIPS activation in 'easy' conditions, while children with high BIS scores had greater aIPS activation in 'hard' conditions.

Moreover, we saw overlapping neural activity among tasks in TPJ, DLPFC and IPS that suggests these regions are an important source for individual differences in the development of executive control. It is worth noting the functional overlap between IOWA and UEA, particularly in TPJ, was related to age, such that we saw an increase in neural activity over development. Importantly, neural activity in IOWA was predictive of EC at 42 months. Although neural activity in UEA was not predictive of EC, behavioral measures in this task were predictive of later EC. Thus, there is evidence that both behavioral measures and neural correlates of attentional disengagement are critical indices of 42-month effortful control.

In the present study, I found that attentional disengagement required involvement from prefrontal and parietal regions of the brain (for similar results see  Csibra et al., 1997, 1998). In contrast to previous work (e.g., Wass & Smith, 2014; Geeraerts et al., 2019; Rothbart, Ellis, Rueda, & Posner, 2003), I found both attentional orienting (disengagement) and executive attention (anticipatory looking) at 30 months are predictors of later EC. Recall that Posner et al. (2014) had reported that early in development, control is primarily driven by the orienting attention network. By 4 years, there is an observed shift in self-regulation such that later forms of control are driven by the executive attention network. Results suggests that by 30 months, children may be in a transitional period where they use both attentional systems to support self-regulation. This is also consistent with the fact that in chapter  2 I did not observe a relationship between children's (aged 2-6 year olds) orienting attention and effortful control. It is possible that the transition toward executive attention has finished by this age, and executive attention plays a primary role in controlling behavior with older children.

In all, the behavioral results suggest pervasive relationships between executive attention and EC. Interestingly, within the temperament literature, effortful control has been equated to reflect individual differences in the efficiency of the executive attention network (Rueda et al., 2011). These results provide partial support to this idea, as the measure of executive attention (UEA) was predictive of individual differences in concurrent and later developing EC. However, when looking at the level of the brain, the neural results suggest that the neural correlates of orienting attention might also play an important role in self-regulation early in development.

Critically, in light of these results, tracking DLPFC and TPJ activation could serve as an informative bio-marker to identify children who are at risk for EC/EF deficits. Recall that in the IOWA task, neural activity but not behavior, was predictive of EC at 42 months. Conversely, in the UEA task I found that behavioral performance, but not neural activity, was predictive of EC at 42 months. These contrasting results highlight the importance of integrating multiple levels of analysis to obtain a more complete picture of emerging developmental cascades. It would be fascinating to expand these results to include measures of structural brain development, which arguably could be more stable than the functional and behavioral measures collected here, albeit harder to collect. Nevertheless, long-term longitudinal data is needed to further explore these complex interactions over development.

There are some limitation of this work. First, among the three measures of executive control used in this work (e.g., MEFS, GW, and parent-reported effortful control), I only found relationships with parent-reported EC. There are a number of factors that could explain this. Notably, MEFS is language heavy and it requires fine motor control to be able to drag the test cards to the target boxes. While performance in MEFS shows a strong linear relationship with age and this task shows good internal consistency and reliability, the requirement of advanced language and fine-motor skills might mask young children's executive control abilities. In contrast to this, the primary measures in this study relied on visual dynamics. Looking patterns, while sometimes noisy, are reliably predictive of young children's abilities. Note also that the first few levels in MEFS are categorization and reverse categorization. These are language-related abilities that might not be strongly related to measures of WM and attention. It could be that as children get older and the rules in MEFS get more abstract, this measure starts to become relevant to the executive function subcomponents measured here. One can imagine that as the levels of abstraction start to exceed children's abilities, for instance, more attention and WM is needed to successfully perform the task. This suggests that this task may struggle to accurately portray executive control in younger children. Future work should examine whether early language and motor ability mediates relationships between attention, WM, and performance in this task in the younger age ranges.

In contrast to the results reported here, performance in the Gift Wrap task has been previously linked to EC. There was a high rate of missing data in this task among the two studies, especially with the younger participants. This could be explained by task priorities as this task was always completed at the end of a session by which time participants -especially younger ones- were sometimes too tired to complete the paradigm.

Conversely, the WM and attention measures were related to executive control as measured by parent-report. Thus, these different cognitive measures are tapping into a factor that resonates with parents' perceptions of their children. Of course, these reports are based on lots of observation time; thus, in terms of real world relevance, these relationships likely provide an important index of how children behave in more naturalistic contexts. A caveat here, however, is that parent reports can be biased. For instance, in both studies, girls had higher effortful control than boys. While this might be reality, it is also possible that parents have biased perceptions of the relationship between effortful control and gender roles. It will be important for future work to examine these issues directly. Ideally, it would be useful to find an objective measure of effortful control that both corroborates parents' perceptions but also corrects for any systematic biases in these perceptions.

Additionally, in the present study I used fNIRS to measure the neural correlates of attention and WM. While this allows us to measure neural activity relatively easily from younger children, and leaves the door open for future work with younger participants, I was only able to measure cortical activity within the outer centimeter or so of cortex. This means that key functions such as error monitoring by the anterior cingulate cortex were out of reach of the fNIRS sensors. Future work using other imaging techniques might allow us to examine how, for instance, functional connectivity in deeper cortical structures relate to emerging executive control abilities.

## 4.1 Conclusion

In conclusion, the present study focused on the development of subcomponents of emerging executive function. Results revealed robust relationships between neural and behavioral measures of hypothesized executive function subcomponents, namely WM and attention. Critically, while performance in the WM task was not directly related to EC, the second study showed that neural activity in IFG, which supported performance in within capacity loads in the VWM task, was predictive of effortful control at 42 months. Attentional control showed robust relationships with concurrent and later developing effortful control at the level of the brain and behavior.

Results suggest that visual dynamics in WM and attention tasks are related to later developing executive control skills. I found remarkable consistency across the two studies. Further, results support the idea that we can use simple visual tasks to measure important indices of executive control across different age ranges. This sets the stage for looking at earlier development to see what measures are predictive of executive control longitudinally.

Specifically, given that these assessments rely on visual dynamics, we can use these same procedures to measure WM and attention in infants as young as four months of age, as previous research has shown that infants this young can complete these tasks (Johnson et al., 1991; Delgado Reyes et al., in rev; Ross-Sheehy et al., 2003). Indeed, our research group is pursuing this idea. We are measuring these cognitive abilities longitudinally over three years with two cohorts: one beginning at six months of age and a second one beginning at 30 months (e.g., participants in the study reported in Chapter 3. In this study we are integrating the same measures used in this thesis. Importantly, all three tasks can be used across both age groups as they rely on simple visual dynamics. Additionally, while pursuing this idea, we are including indices of brain structure and well as other general measures of cognition. We are also collecting data on parent-child interactions, language, sleep and motor development. Thus, we will be able to look at relationships across different domains of child development.

In the end, we expect to be able to answer questions about the the long-term predictive power of these visual measures and how these measures relate to both structural and functional brain development. In particular, we will be able to compare, across two longitudinal cohorts, the predictive power of these measures within the first four years of life. If these relationships remain stable over development this would provide strong evidence that looking dynamics should be a focus for future work, further validating the cross-sectional results reported in chapter 2. This could set the stage for early intervention efforts targeting how infants deploy VWM and attention in real-world contexts.

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# Appendix A

Table A.1: VWM-PL Regression results using proportion looking to change as the criterion

| | **Chisq** | **Df** | **Pr(>Chisq)** | |
|---|---|---|---|---|
| (Intercept) | 2.8961 | 1 | 0.089 | . |
| ot1 | 1.8189 | 1 | 0.177 | |
| ot2 | 2.1049 | 1 | 0.147 | |
| ot3 | 0.8317 | 1 | 0.362 | |
| ot4 | 2.9896 | 1 | 0.084 | . |
| ot5 | 0.0818 | 1 | 0.775 | |
| ot6 | 0.1067 | 1 | 0.744 | |
| ot7 | 5.9241 | 1 | 0.015 | * |
| Age | 0.1008 | 1 | 0.751 | |
| Load | 0.3193 | 2 | 0.852 | |
| ot1 : Age | 7.1448 | 1 | 0.008 | ** |
| ot2 : Age | 10.7019 | 1 | 0.001 | ** |
| ot3 : Age | 11.0722 | 1 | <0.001 | *** |
| ot4 : Age | 0.1711 | 1 | 0.679 | |
| ot5 : Age | 0.0889 | 1 | 0.766 | |
| ot6 : Age | 2.0064 | 1 | 0.157 | |
| ot7 : Age | 1.3328 | 1 | 0.248 | |
| ot1 : Load | 1032.6241 | 2 | <0.001 | *** |
| ot2 : Load | 1046.8993 | 2 | <0.001 | *** |
| ot3 : Load | 20.729 | 2 | <0.001 | *** |
| ot4 : Load | 328.3144 | 2 | <0.001 | *** |
| ot5 : Load | 9.9062 | 2 | 0.007 | ** |
| ot6 : Load | 127.3394 | 2 | <0.001 | *** |
| ot7 : Load | 108.3169 | 2 | <0.001 | *** |
| Age : Load | 0.6677 | 2 | 0.716 | |
| ot1 : Age : Load | 1284.2846 | 2 | <0.001 | *** |
| ot2 : Age : Load | 1233.8028 | 2 | <0.001 | *** |
| ot3 : Age : Load | 527.6822 | 2 | <0.001 | *** |
| ot4 : Age : Load | 475.3772 | 2 | <0.001 | *** |
| ot5 : Age : Load | 105.4258 | 2 | <0.001 | *** |
| ot6 : Age : Load | 417.6869 | 2 | <0.001 | *** |
| ot7 : Age : Load | 29.4496 | 2 | <0.001 | *** |

Table A.2: T-tests comparing change preference score against chance. Chance for VWM-PL = 0.50; chance for VWM-4Sq = 0.0

| *Task* | *Age Group* | *Load* | *t* | *df* | *p-value* | *95 % CI* |
|---|---|---|---|---|---|---|
| VWM-PL | younger | ss2 | 0.899 | 21 | 0.378 | 0.4570190 - 0.6085648 |
| | | ss4 | 1.7263 | 21 | 0.099 | 0.4864647 - 0.6457855 |
| | | ss6 | 2.4709 | 21 | 0.022* | 0.5129972 - 0.6511442 |
| | older | ss2 | 1.8146 | 21 | 0.084 | 0.4933237 - 0.5980852 |
| | | ss4 | -0.056737 | 21 | 0.955 | 0.4276570 - 0.5685004 |
| | | ss6 | 0,45714 | 21 | 0.652 | 0.4370389 - 0.5984399 |
| VWM-4Sq | younger | ss2 | 4.1448 | 27 | 0.000*** | 0.06214231 - 0.18398324 |
| | | ss3 | 1.4354 | 26 | 0.163 | -0.02682762 - 0.15102263 |
| | | ss4 | 1.7164 | 28 | 0.097 | -0.0106747 - 0.121055 |
| | older | ss2 | 3.9623 | 28 | 0.000*** | 0.06371747 - 0.20010699 |
| | | ss3 | 3.3306 | 29 | 0.002** | 0.04816508 - 0.20143582 |
| | | ss4 | 2.1995 | 27 | 0.036* | 0.006325875 - 0.174068882 |

Table A.3: VWM-4Sq Regression results using proportion looking to change as the criterion

| | **Chisq** | **Df** | **Pr(>Chisq)** | |
|---|---|---|---|---|
| (Intercept) | 65.0984 | 1 | <0.001 | *** |
| ot1 | 0.9908 | 1 | 0.320 | |
| ot2 | 8.8953 | 1 | 0.003 | ** |
| ot3 | 17.9353 | 1 | <0.001 | *** |
| ot4 | 3.3172 | 1 | 0.069 | . |
| ot5 | 6.9122 | 1 | 0.009 | ** |
| ot6 | 0.7201 | 1 | 0.396 | |
| ot7 | 6.4215 | 1 | 0.011 | * |
| Load | 52774.6243 | 2 | <0.001 | *** |
| Age | 4.0414 | 1 | 0.044 | * |
| Load : Age | 701.4685 | 2 | <0.001 | *** |
| ot1 : Load | 41.5515 | 2 | <0.001 | *** |
| ot1 : Age | 0.0816 | 1 | 0.775 | |
| ot2 : Load | 736.5423 | 2 | <0.001 | *** |
| ot2 : Age | 4.8415 | 1 | 0.028 | * |
| ot3 : Load | 519.7043 | 2 | <0.001 | *** |
| ot3 : Age | 1.5667 | 1 | 0.211 | |
| ot4 : Load | 106.9538 | 2 | <0.001 | *** |
| ot4 : Age | 0.0976 | 1 | 0.755 | |
| ot5 : Load | 498.5227 | 2 | <0.001 | *** |
| ot5 : Age | 1.9412 | 1 | 0.164 | |
| ot6 : Load | 94.8016 | 2 | <0.001 | *** |
| ot6 : Age | 1.5264 | 1 | 0.217 | |
| ot7 : Load | 24.0644 | 2 | <0.001 | *** |
| ot7 : Age | 7.2301 | 1 | 0.007 | ** |
| ot1 : Load : Age | 945.6375 | 2 | <0.001 | *** |
| ot2 : Load : Age | 51.1313 | 2 | <0.001 | *** |
| ot3 : Load : Age | 149.8029 | 2 | <0.001 | *** |
| ot4 : Load : Age | 71.5655 | 2 | <0.001 | *** |
| ot5 : Load : Age | 52.8249 | 2 | <0.001 | *** |
| ot6 : Load : Age | 363.4379 | 2 | <0.001 | *** |
| ot7 : Load : Age | 18.3777 | 2 | <0.001 | *** |

Table A.4: Iowa task: Regression results using BIS score as the criterion

| | **BIS score** | | |
|---|---|---|---|
| *Predictors* | *Estimates* | *CI* | *p* |
| (Intercept) | 0.07 | -0.05 – 0.18 | 0.261 |
| Age (in days) | 0.15 | 0.03 – 0.26 | **0.013** |
| Double | 0.06 | -0.05 – 0.17 | 0.285 |
| Control | 0.33 | 0.22 – 0.44 | **<0.001** |
| Invalid | -1 | -1.11 – -0.88 | **<0.001** |
| Competition | -0.31 | -0.38 – -0.25 | **<0.001** |
| Age x Double | -0.02 | -0.13 – 0.09 | 0.736 |
| Age x Control | 0.12 | 0.00 – 0.23 | **0.044** |
| Age x Invalid | -0.18 | -0.29 – -0.07 | **0.002** |
| Age x Competition | 0.05 | -0.02 – 0.11 | 0.154 |
| Double x Competition | -0.07 | -0.18 – 0.04 | 0.237 |
| Control x Competition | -0.18 | -0.29 – -0.06 | **0.002** |
| Invalid x Competition | 0.27 | 0.16 – 0.39 | **<0.001** |
| Age x Double x Competition | -0.05 | -0.16 – 0.07 | 0.418 |
| Age x Control x Competition | 0.06 | -0.05 – 0.17 | 0.31 |
| Age x Invalid x Competition | 0.01 | -0.10 – 0.12 | 0.851 |
| **Random Effects** | | | |
| $\sigma^2$ | 0.87 | | |
| $\tau 00_{\mathrm{ID}}$ | 0.22 | | |
| ICC | 0.2 | | |
| $\mathrm{N}_{\mathrm{ID}}$ | 101 | | |
| Observations | 791 | | |
| Marginal $\mathrm{R}^2$ / Conditional $\mathrm{R}^2$ | 0.327 / 0.464 | | |

Table A.5: Standardized coefficients from path analysis.

| lhs | rhs | B | SE | Z | p-value | Beta | |
|---|---|---|---|---|---|---|---|
| HLP | Age | 2.116 | 23.156 | 0.091 | 0.927 | 1.245 | |
| HLP | UEA | -0.914 | 62.398 | -0.015 | 0.988 | -0.538 | |
| HLP | Iowa_NoComp | 0.259 | 28.378 | 0.009 | 0.993 | 0.153 | |
| HLP | Iowa_Comp | 0.069 | 27.16 | 0.003 | 0.998 | 0.041 | |
| HLP | lWM | -0.089 | 220.45 | 0 | 1 | -0.053 | |
| HLP | hWM | 3.147 | 90.883 | 0.035 | 0.972 | 1.86 | |
| HLP | EC | -0.094 | 325.083 | 0 | 1 | -0.037 | |
| EC | Age | -0.122 | 0.621 | -0.196 | 0.845 | -0.179 | |
| EC | UEA | 0.166 | 0.079 | 2.103 | 0.035 | 0.244 | * |
| EC | Iowa_NoComp | -0.017 | 0.074 | -0.231 | 0.817 | -0.025 | |
| EC | Iowa_Comp | -0.061 | 0.079 | -0.767 | 0.443 | -0.089 | |
| EC | lWM | 0.042 | 0.079 | 0.53 | 0.596 | 0.062 | |
| EC | hWM | -0.015 | 0.1 | -0.155 | 0.877 | -0.023 | |
| EC | HLP | 0.073 | 0.455 | 0.16 | 0.873 | 0.181 | |
| GW | Age | 1.954 | 5.646 | 0.346 | 0.729 | 1.382 | |
| GW | UEA | 0.808 | 7.867 | 0.103 | 0.918 | 0.572 | |
| GW | EC | -6.719 | 49.298 | -0.136 | 0.892 | -3.228 | |
| GW | Iowa_Comp | -0.298 | 3.304 | -0.09 | 0.928 | -0.212 | |
| HLP | EC | 0.096 | 134.456 | 0.001 | 0.999 | 0.046 | |
| Age | UEA | 0.177 | 0.097 | 1.827 | 0.068 | 0.18 | |
| UEA | lWM | 0.146 | 0.107 | 1.366 | 0.172 | 0.147 | |
| UEA | hWM | 0.232 | 0.108 | 2.15 | 0.032 | 0.234 | * |
| Age | Iowa_NoComp | -0.09 | 0.102 | -0.887 | 0.375 | -0.091 | |
| Iowa_NoComp | lWM | 0.147 | 0.11 | 1.335 | 0.182 | 0.148 | |
| Iowa_NoComp | hWM | -0.04 | 0.105 | -0.383 | 0.702 | -0.04 | |
| Age | Iowa_Comp | -0.08 | 0.106 | -0.75 | 0.453 | -0.08 | |
| Iowa_Comp | lWM | -0.074 | 0.109 | -0.679 | 0.497 | -0.074 | |
| Iowa_Comp | hWM | -0.016 | 0.107 | -0.154 | 0.878 | -0.017 | |
| HLP | lWM | 0.267 | 208.73 | 0.001 | 0.999 | 0.082 | |
| Age | lWM | -0.008 | 0.101 | -0.082 | 0.935 | -0.008 | |
| lWM | mWM | 0.012 | 0.101 | 0.123 | 0.902 | 0.012 | |
| GW | lWM | 0.241 | 2.357 | 0.102 | 0.918 | 0.05 | |
| HLP | hWM | -2.908 | 81.235 | -0.036 | 0.971 | -0.896 | |
| Age | hWM | -0.175 | 0.102 | -1.717 | 0.086 | -0.177 | |
| hWM | mWM | -0.053 | 0.101 | -0.527 | 0.598 | -0.054 | |
| GW | hWM | 0.167 | 1.675 | 0.1 | 0.92 | 0.035 | |
| Age | mWM | 0.031 | 0.101 | 0.304 | 0.761 | 0.031 | |
| GW | Age | -1.096 | 5.448 | -0.201 | 0.841 | -0.227 | |
| HLP | GW | 1.845 | 984.773 | 0.002 | 0.999 | 0.117 | |
| EC | GW | 2.901 | 20.87 | 0.139 | 0.889 | 0.934 | |
| HLP | HLP | 10.586 | 598.265 | 0.018 | 0.986 | 3.718 | |
| EC | EC | 0.409 | 0.079 | 5.195 | 0 | 0.9 | |
| GW | GW | 23.559 | 299.197 | 0.079 | 0.937 | 11.96 | |
| Age | Age | 0.986 | 0.136 | 7.271 | 0.0000 | 1 | |
| UEA | UEA | 0.986 | 0.136 | 7.243 | 0.0000 | 1 | |
| Iowa_NoComp | Iowa_NoComp | 0.989 | 0.141 | 7.007 | 0.0000 | 1 | |
| Iowa_Comp | Iowa_Comp | 0.99 | 0.145 | 6.848 | 0.0000 | 1 | |
| lWM | lWM | 1.003 | 0.148 | 6.775 | 0.0000 | 1 | |
| hWM | hWM | 0.995 | 0.144 | 6.922 | 0.0000 | 1 | |
| mWM | mWM | 0.988 | 0.143 | 6.9 | 0.0000 | 1 | |

Table A.6: VWM Regression results using proportion looking to change side as the criterion

| | **Chisq** | **Df** | **Pr(>Chisq)** | |
|---|---|---|---|---|
| (Intercept) | 2.8557 | 1 | 0.091 | . |
| ot1 | 7.4334 | 1 | 0.006 | ** |
| ot2 | 19.6876 | 1 | 0.000 | *** |
| ot3 | 2.8437 | 1 | 0.092 | . |
| ot4 | 4.7317 | 1 | 0.030 | * |
| ot5 | 16.2555 | 1 | 0.000 | *** |
| ot6 | 579.2449 | 1 | <0.001 | *** |
| ot7 | 7.8735 | 1 | 0.005 | ** |
| Condition | 1.1505 | 1 | 0.283 | |
| meanAge_s | 0.0016 | 1 | 0.968 | |
| ot1:Condition | 168.3834 | 1 | <0.001 | *** |
| ot2:Condition | 1789.6097 | 1 | <0.001 | *** |
| ot3:Condition | 65.638 | 1 | 0.000 | *** |
| ot4:Condition | 53.1641 | 1 | 0.000 | *** |
| ot5:Condition | 536.1142 | 1 | <0.001 | *** |
| ot6:Condition | 336.0527 | 1 | <0.001 | *** |
| ot7:Condition | 38.3165 | 1 | 0.000 | *** |
| ot1:meanAge_s | 1.9597 | 1 | 0.162 | |
| ot2:meanAge_s | 3.6141 | 1 | 0.057 | . |
| ot3:meanAge_s | 6.4089 | 1 | 0.011 | * |
| ot4:meanAge_s | 7.5397 | 1 | 0.006 | ** |
| ot5:meanAge_s | 1.6101 | 1 | 0.204 | |
| ot6:meanAge_s | 0.211 | 1 | 0.646 | |
| ot7:meanAge_s | 76.6695 | 1 | <0.001 | *** |
| Condition:meanAge_s | 0.1849 | 1 | 0.667 | |
| ot1:Condition:meanAge_s | 174.9173 | 1 | <0.001 | *** |
| ot2:Condition:meanAge_s | 422.8057 | 1 | <0.001 | *** |
| ot3:Condition:meanAge_s | 784.8756 | 1 | <0.001 | *** |
| ot4:Condition:meanAge_s | 236.4213 | 1 | <0.001 | *** |
| ot5:Condition:meanAge_s | 24.8933 | 1 | <0.001 | *** |
| ot6:Condition:meanAge_s | 0.0592 | 1 | 0.808 | |
| ot7:Condition:meanAge_s | 89.5376 | 1 | <0.001 | *** |

Table A.7: T-tests comparing change preference score against chance. Chance = 0.50.

| *Task* | *Age Group* | *Load* | *t* | *df* | *p-value* | *95 % CI* |
|---|---|---|---|---|---|---|
| VWM | younger | ss2 | 3.3095 | 34 | 0.002** | 0.5249918 - 0.6045222 |
| | | ss4 | 1.2698 | 34 | 0.213 | 0.4828859 - 0.5741179 |
| | | ss6 | -1.5105 | 34 | 0.140 | 0.4146043 - 0.5125775 |
| | older | ss2 | 4.7037 | 40 | 0.000*** | 0.5479549 - 0.6202135 |
| | | ss4 | 3.2594 | 40 | 0.002** | 0.5247260 - 0.6054342 |
| | | ss6 | 2.2209 | 40 | 0.032* | 0.5029877- 0.5634136 |

Table A.8: fNIRS ANOVA results for VWM task.

| Effect | Cluster No. | ROI | Hemi | Size ($\text{mm}^3$) | Center of Mass |  |  | Brain * Behavior |
|---|---|---|---|---|---|---|---|---|
|  |  |  |  |  | x | y | z |  |
| Age x Load x Hb | 1 | IFG | R | 1640 | -42.8 | -1 | 10.7 |  |
|  | 2 | VOC | L | 952 | 44.3 | 60.2 | -2.4 | Age:Prop*;<br>Cond6:Prop***;<br>Age:Cond6:Prop*** |
|  | 3 | IPS | R | 448 | -20.1 | 52.9 | 47.4 |  |
| Age x Hb | 1 | VOC | L | 1536 | 30.5 | 69.3 | -4.4 | Condition6:Prop**;<br>Age:Condition6:Prop* |
| Hb | 1 | MFG | L | 416 | 48.2 | -2.3 | 16.2 |  |

# Table A.9: fNIRS ANOVA Results from IOWA task

| Effect | Cluster No. | ROI | Hemi | Size (mm$^3$) | Center of Mass | | | Brain * Behavior |
|---|---|---|---|---|---|---|---|---|
| | | | | | x | y | z | |
| Age x Congruency x Competition x Hb | 1 | DLPFC | L | 3976 | 18.7 | -26.6 | 26.7 | bis*;<br>Age:bis *;<br>Age:Comp:bis*;<br>Age:CongrDouble:bis**;<br>Age:Comp:CongrDouble:bis* |
| | 2 | DLPFC | R | 2088 | -26.8 | -18 | 32.7 | CongrControl:bis***;<br>Age:CongrControl:bis *;<br>Comp:CongrControl:bis** |
| | 3 | TPJ | L | 744 | 45.2 | 36.2 | 23.5 | Age:Congr:bis* |
| | 4 | DLPFC | R | 496 | -18.9 | -40 | 18.6 | |
| | 5 | aIPS | L | 376 | 31.7 | 32.8 | 49.2 | Age:NoComp:CongrValid:bis*** |
| Age x Competition x Hb | 1 | | R | 1496 | -41.6 | 25.9 | -1.3 | |
| | 2 | MFG | R | 1040 | -41.8 | 7.3 | 33.2 | |
| | 3 | MFG | L | 800 | 34 | 23.2 | 39.8 | |
| | 4 | aIPS | L | 400 | 34 | 23.2 | 39.8 | |
| | 5 | | R | 368 | -49.8 | 19.5 | 16.3 | |
| Age x Congruency x Hb | 1 | | R | 1216 | -36.5 | 20.8 | 4.7 | |
| Age x Hb | 1 | IPS | R | 1296 | -30.4 | 57.9 | 38.1 | |
| | 2 | VOC (adjacent) | R | 768 | -21.7 | 75.6 | 4.1 | |
| | 3 | | L | 584 | 20.5 | 35.2 | 51.9 | |
| Hb | 1 | DLPFC | R | 592 | -41.11 | -14.3 | 33.4 | Age:bis*;<br>CongrControl:bis **;<br>Age:CongrControl:bis***;<br>Age:CongrInvalid:bis*;<br>Age:CongrDouble:bis *;<br>CongrControl:Comp:bis*;<br>Age:CongrControl:Comp:bis* |
| | 2 | aIPS | L | 472 | 26.2 | 22.5 | 41.9 | |

## Table A.10: fNIRS ANOVA Results from UEA task

| Condition | Cluster No. | Effect | ROI | Hemi | Size ($mm^3$) | Center of Mass x | Center of Mass y | Center of Mass z | Brain * Behavior |
|---|---|---|---|---|---|---|---|---|---|
| Anticipatory Looking | 1 | Age x Hb | IFG (adjacent) | L | 976 | 19.7 | -20.6 | 2.6 | |
| | 1 | Age x AL x Hb | STG | L | 664 | 37.6 | 29.4 | 10.1 | |
| Disengagement | 1 | Hb | TPJ(adjacent) | L | 392 | 42.4 | 39 | 19.6 | meanAge_s:bis*** |
| | 1 | Age x Hb | left executive control network(S/MFG) | L | 1784 | 12.2 | -24 | 28 | |