Development of Executive Functions: Neurocognitive mechanisms and plasticity in childhood

Keertana Ganesan

Supervisor: Prof. Nikolaus Steinbeis

Psychology and Language Sciences

University College London

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I, Keertana Ganesan, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

Executive functions/cognitive control (namely inhibition, working memory and cognitive flexibility) support flexible goal-directed behaviour. Crucially, good executive functions in childhood have been linked with a range of positive social and mental health outcomes. Therefore, the need to understand and improve it, has been of immense interest. Although considerable efforts have been made to improve executive functions in childhood, the literature has shown limited success. The aim of this thesis was to understand and improve executive functions using a gold-standard approach. The first study used a multi-measurement approach to examine the neural underpinnings of executive functions in childhood finding only correlates for factors of working memory and shifting. The second study compared the efficacy of training targeting two different mechanisms to train executive functions; showing that inhibition-based training was more successful at producing improvements in cognitive control than context monitoring training. Using inhibition as a training mechanism, the third study investigated transfer into other executive functions. We found that our training was effective in improving strategic slowing, as indicated by increases in reaction times in the experimental group. In the fourth study, we examined the efficacy of cognitive control training in producing transfer into a real-world outcome. We found improvements in attentional control in the experimental group, and found functional activity in the inhibition network to be an important predictor of such improvements. Finally, in the fifth study, we explored effort-related decision making in children. Specifically, I find that children of all ages are able to avoid effort when effort cues are made explicit. I discuss the theoretical implications of our findings and future directions for the field for training studies.

Impact statement

Cognitive control supports daily and long-term goals. Childhood cognitive control is an important predictor for later wellbeing. Therefore, interventions have focused on boosting it but have produced mixed findings. Part of this may be due to methodological issues surrounding the measurement of executive functions as well as the design of cognitive control interventions. In this thesis, a multi-measurement approach was used to measure executive functions. Additionally, a gold-standard training protocol which was varied, adaptive and gamified was used to investigate training improvements.

This thesis reports a few key findings. First, this thesis found that only unique correlates of working memory and shifting were identified. Second, this thesis showed the privileged role that inhibition demonstrated as a target mechanism for interventions. Thirdly, this thesis found that training produced improvements only in reaction time indices of executive functions, but not error rates. Fourthly, through training, this thesis found improvements in a real-world outcome (attentional control). Finally, this thesis found that children of all ages are able to avoid effort when effort cues were made explicit.

These findings contribute significantly to current models of executive functioning by clarifying the role of inhibition as a core process that may represent general executive functioning. Further, through a gold-standard training protocol, this thesis demonstrates the extent of transfer that occurs in other executive functions and real-world domains. This has important implications for future research, suggesting that inhibition-based interventions may hold promise. Finally, this thesis helps clarify previous disagreement in the literature on effort-related decision making in children, showing the key role saliency of effort cues play.

Ultimately, this may contribute to the practical application of cognitive control interventions in developmental populations.

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Chapter 1. Introduction

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On a daily basis, we are flooded with goals and decisions that require careful thought and flexibility. Think about a dinner party that you may be organising. This requires careful planning of the ingredients and party supplies you may have to pick up from various stores. At each store, you need to keep in mind the particular items required (e.g. eggs from the supermarket rather from a party supply store). The supermarket has run low on their stock of eggs, requiring you to flexibly adapt your behaviour to either change your recipe or find a replacement. At the supermarket, you may be distracted with other ingredients that pique your interest and you need to successfully resist these urges. This one example sums up how executive functioning plays a crucial role in our lives aiding our goals (Figure 1-1). For the purposes of our thesis, we will use the terms executive functions and cognitive control interchangeably in line with previous literature (Diamond, 2013). This chapter provides an in-depth look at the role of executive functions, its development and intervention attempts. Finally, an examination of executive functions through a value-based account is provided.

Figure 1-1. Example of cognitive control supporting goals. (a) Planning of a party carefully thought of the elements a party requires. (b) After planning carefully, supplies and ingredients need to be noted down for each individual shop. (c) One of the important items for the cake you plan to make is eggs but when they are not available (d) you need to flexibly adapt your behaviour to either find a replacement ingredient or bake another dessert.

1.1. The role of Executive Functions

Achieving one’s goals, be they immediate or long-term, requires control of thoughts and actions. Executive functions (EFs) describe a cluster of cognitive operations that enable such goal-directed behaviour (Botvinick & Braver, 2015; Diamond, 2013) through stopping pre-potent responses and impulses (inhibition), manipulating and remembering goal-related information (working memory) and responding flexibly to changes in the environments (shifting). EFs during infancy and childhood have been of particular interest to researchers and clinicians as they are predictive of later emotional, behavioural, and social wellbeing (Moffitt et al., 2011).

1.1.1. Inhibition

Inhibition has been found to be one of the core aspects of cognitive control (Diamond, 2002). Inhibition describes the ability to stop a pre-potent response (Munakata et al., 2011). This is arguably crucial in enabling control over behaviour, emotions, and attention. In our initial example for instance, our ability to inhibit distractions in our environment is crucial in guiding our behaviour (e.g. only picking up the necessary items at the grocery store). It should be noted that there is debate on the types of inhibition and whether they are mechanistically the same construct. For example, some papers have coined the terms ‘global inhibition’ vs ‘competitive inhibition’ (Hendry et al., 2022; Munakata et al., 2011). The former is conceptualised as the stopping of an action on demand, while the latter is employed when an alternative response should be given (Hendry et al., 2022; Munakata et al., 2011). Nevertheless, inhibition emerges early and has been reported to be the first developing executive function (Fiske & Holmboe, 2019). Indeed, children as young as four have been found to exhibit inhibition abilities, with some evidence pointing to its emergence in infancy (Best et al., 2009; Best & Miller, 2010; Friedman et al., 2011; Garon et al., 2008, 2014).

We acknowledge the overextension of the term inhibition in the literature, and it should be noted that inhibition measured in laboratory settings may be a different construct to trait measures of self-control (Baumeister, 2014; Friedman & Miyake, 2004; Saunders et al., 2018). Arguably, task-based inhibition is narrower and domain specific whereas self-control (self-reported) is more general, representing control in a wide range of contexts (Duckworth & Tsukayama, 2015; Haws et al., 2016; Roberts et al., 2014; Wennerhold & Friese, 2020). In the 'real-world', contexts requiring self-control that depend on inhibition could vary from the inhibition of attention to the inhibition of a response. For instance, in a classroom setting, children may employ self-control to inhibit distractions from friends through efficient attentional allocation. They may also employ self-control to stop their impulse to blurt an answer out. Arguably, there are qualitative differences between these types of behaviour, implying that self-control may be more muti-faceted (de Ridder et al., 2011). On the other hand, inhibition tasks typically require 'motoric' stopping – this could explain the lack of correlations observed between the two (Eisenberg et al., 2019; Enkavi et al., 2019; Saunders et al., 2018). This does not mean that task-measures are meaningless per se, as task-related inhibition could still be useful in measuring variability in individual performance that self-reported questionnaire measures are unable to do (Cañigueral et al., preprint.; Thompson et al., 2021). Instead, this suggests that caution is needed in the terminology. For our purposes, in this thesis, we conceptualise inhibition as 'motoric' stopping or response inhibition where a pre-potent (i.e. favoured/biased) response needs to be withheld or stopped. This is measured through a range of different tasks (i.e. stop-signal, stroop, flanker).

1.1.2. Working memory

Another process of cognitive control is working memory. Working memory refers to the storage and manipulation of information (Baddeley & Hitch, 1974). Working memory is especially crucial in learning and education (Alloway, 2006; Cowan, 2013), for instance, helping support the manipulation of numbers in mathematics (Bull et al., 2011). While there are a range of frameworks conceptualising working memory (Baddeley, 1998), the general consensus is that working memory is limited and is supported by a variety of processes such as attention (Baddeley, 2012; Eriksson & Häggström, 2014). Unsurprisingly, correlates between working memory and fluid intelligence are well-established, predicting reasoning ability (Jarrold & Bayliss, 2008). Specifically, this thesis has focused on examining working memory through measures of accuracy and memory span (i.e. Corsi block tapping, n-back).

1.1.3. Shifting

Shifting is the last core function of cognitive control (Diamond, 2013). It is defined as one’s ability to adjust their behaviour according to a changing environment (Armbruster et al., 2012; Dajani & Uddin, 2015; Scott, 1962). Often, it is considered to be a more complex function as it requires individuals to disengage from a current rule or task, reconfigure to a new task and implement the appropriate response or rule. Indeed, this may explain its longer developmental trajectory, developing even into adolescence (Davidson et al., 2006). Shifting is frequently implemented in our daily lives. For instance, shifting is required for us to effectively multitask and ensuring the appropriate actions are performed for each individual task. In this thesis, shifting has been examined through measures of accuracy and reaction times (i.e. cognitive flexibility, flanker shifting).

1.1.4. Unity and Diversity Theory

There are some clear parallels between the EFs and how they may function to support each other. For instance, let us revisit the example of picking up eggs at the supermarket where individuals need to inhibit distractions. Arguably for this, the other EFs are employed along with inhibition. The item could be seen as a contextual cue which individuals have to monitor to be able to execute the correct response (i.e. coordinate behaviour to pick up eggs, inhibit behaviour to resist picking up bread), involving shifting abilities (Dajani & Uddin, 2015). Inhibition is employed to effectively stop the alternate response that is inappropriate to that particular context while working memory is used to remember the appropriate responses for each context (Baddeley, 2012; Munakata et al., 2011). Given how the different EFs work in conjunction to support daily goals and behaviour, to what extent are these functions distinct? Could they simply be subserved by the same set of mechanisms, representing a unitary construct?

While early models viewed EF as a unitary construct (Baddeley, 1996; Norman & Shallice, 1986; Shallice, 1988), specific dissociable deficits were observed in patient populations (e.g. inability to perform a shifting task but ability to perform a working memory task; Duncan et al., 2010; Stuss & Alexander, 2000). This contradicts a unitary account of EF as we would expect deficits in all functions. A more popular theory that has emerged in the literature is the unity and diversity theory of EF (Miyake et al., 2000). This theory suggests that while the three functions of cognitive control are separable, they also have shared commonality (Karr et al., 2018; Miyake et al., 2000; Miyake & Friedman, 2012). Specifically, this suggests that EF is a multi-faceted construct with distinct functions. We review the behavioural and neural evidence in support of this, offering explanations for some inconsistencies reported in the literature.

1.1.4.1. Behavioural Evidence

The behavioural evidence supporting the unity and diversity theory is mixed. While a range of studies do find robust links between the functions of cognitive control (Kim et al., 2017; Mulder et al., 2011), other studies report low intercorrelations between cognitive control tasks (Collette et al., 2006; Miyake et al., 2000). Arguably, however, this could be partially confounded by measurement impurity issues (Miyake & Friedman, 2012; Snyder et al., 2015). For example, indices from a single shifting task may represent shifting abilities as well as task-specific skills (e.g. comprehension or colour recognition abilities). This could explain the lack of correlations between cognitive control measures as they do not purely represent executive functions. Instead, examining multi-measurement studies that create latent factors of cognitive control find more evidence for unity amongst the EFs (although note that more unidimensionality is observed in child than adult populations; Huizinga et al., 2006; Karr et al., 2018; Messer et al., 2018, 2022). Indeed, developmental studies suggest that in childhood EFs may be less specialised, as evidenced by the EFs being best explained by a unitary model in childhood (Karr et al., 2018; Messer et al., 2022). This view is not uncontentious as other studies find a two-factor fit encompassing inconsistent combinations (e.g. inhibition/shifting and memory factors; inhibition and memory/shifting factors; Huizinga et al., 2006; Karr et al., 2018; Messer et al., 2018, 2022). Inconsistent findings may be partially attributed to the differences in exact measures used, sample sizes and age group of samples. Nevertheless, this emphasises the importance of taking a multi-measurement approach to measuring EFs – and Chapters 2 and 4 follow this approach.

1.1.4.2. Neural Evidence

In addition to shared neural substrates, separable brain regions related to the different domains of EF (i.e. inhibition, working memory, shifting) have been identified (Collette et al., 2006; McKenna et al., 2017). Specifically, amongst all domains activation was present in the bilateral frontal-parietal network (FPN), which has been proposed to be involved in modulating EFs in a wide array of tasks (Cole et al., 2013; McKenna et al., 2017). Separable activity in regions such as the anterior cingulate cortex and inferior frontal gyrus were found to be particularly associated with inhibition (Cole et al., 2013; He et al., 2021; McKenna et al., 2017). In line with this, one study found that while working memory was associated with cortical thinning in areas such as the superior parietal cortex, inhibition was primarily associated with cortical thinning in occipital and parietal regions such as the pericalcarine cortex (Tamnes et al., 2010). These findings are consistent with behavioural data reporting unitary yet distinct domains of executive functions and may explain the differential developmental trajectories of executive function domains (Davidson et al., 2006). We note however, some inconsistency in the literature regarding neural substrates that underlie inhibition. Specifically, while single-measurement studies have reported a range of regions underlying inhibition, one meta-analysis found activation of inhibition to be completely overlapping with general executive functioning (McKenna et al., 2017; Tamnes et al., 2010). Again, this could be explained by task impurity issues where any neural correlates identified could be task specific (i.e. in single measure studies) rather than a representation of measured EF (Snyder et al., 2015). Additionally, neural correlates could represent overlap between executive functions rather than the one argued to measure. Indeed, many tasks that measure inhibition use a design where a stop vs go response needs to be given depending on the cue provided. As highlighted multiple EFs could be recruited for this, confounding neural-task correlates. This highlights the need for a multi-measurement approach that creates latent factors of EFs – an approach the present thesis employs. Specifically, Chapter 2 uses a latent factor approach to EFs to reliably test for brain structure associations.

1.1.5. Relevance to clinical behaviours and other outcomes

1.1.5.1. Clinically relevant behaviours

The strong interest in executive functions can be partially attributed to the clinical relevance of dysfunctional cognitive control. Indeed, many clinically relevant behaviours such as attention deficit hyperactivity disorder (ADHD) and obsessive-compulsive disorder (OCD) are characterised by impairments in cognitive control (Blair & Razza, 2007; Mar et al., 2022; Wodka et al., 2007). For instance, ADHD is characterised by deficits in sustained attention, impulsivity, and hyperactivity (Cabral et al., 2020; American Psychiatric Association, 2013). Multiple studies and meta-analyses have found that patients with ADHD display range of cognitive control impairments (i.e. inhibition, working memory and shifting) even after accounting for other confounders (Metin et al., 2012; Pennington & Ozonoff, 1996; Willcutt et al., 2005). Additionally, other mental health problems such as post-traumatic stress disorder (PTSD), depression and anxiety have been found to be exacerbated and characterised by EF deficits (Bardeen et al., 2022; Gustavson et al., 2018; Hsu et al., 2015). Individuals with EF deficits have poorer attentional control that may led to dysfunctional cognitive styles conferring risk to mental health problems (Gustavson et al., 2018; Hsu et al., 2015).

1.1.5.2. Social and economic functioning

Apart from its clinical relevance, executive dysfunction has been found to be a mediator of social problems in patient groups (Riggs et al., 2006; Tseng & Gau, 2013). In the school setting, this exhibits as children unable to get along with peers or function in a social group at school (Tseng & Gau, 2013). For instance, children with EF impairments may be less likely to wait their turn to speak which may lead to peers disliking them. Strikingly, these poorer outcomes are pervasive and long lasting into adulthood. In adulthood, poorer EF has been associated with antisocial and criminal behaviour (Meijers et al., 2015; Morgan & Lilienfeld, 2000; Ogilvie et al., 2011). One meta-analysis found poorer cognitive control in violent offenders as compared to non-violent offenders (Meijers et al., 2017). Individuals with EF deficits may have a reduced ability to be able to stop their behaviour and have the inability to carefully assess punishment and reward associated with their behaviour. This may increase their chances of engaging in socially inappropriate or risky behaviour. Additionally, adults with poorer EFs (both in childhood and adulthood) have been reported to experience unemployment and poorer personal finances (Caspi et al., 1998; Moffitt et al., 2011). Incapability to prioritise and plan efficiently, which are supported by EFs, may lead to poorer financially decisions or the inability to stay in employment due to poor performance (i.e. performance may depend on meeting deadlines which is supported by EFs). This highlights the particular role cognitive control may play in supporting better social and economic functioning.

1.1.6. Summary

Cognitive control helps us achieve daily and future goals by supporting flexible behaviour. Dysfunctional cognitive control is associated with poorer mental, behavioural and social outcomes. An abundance of literature suggests that while the functions of EFs share commonality, they are separable. Crucially, the literature highlights the necessity for multiple measurements to be utilised to reliably measure EFs – an approach that the current thesis takes.

1.2. Executive Functions in development

1.2.1. Development of Cognitive control

1.2.1.1. Behavioural Evidence

Indicators of EFs emerge as early as infancy with protracted development into early adulthood (Wiebe & Karbach, 2017). EFs develop particularly rapidly during early and middle childhood, before growing steadily in adolescence (Davidson et al., 2006; Fiske & Holmboe, 2019; Garon et al., 2014). Indeed, multiple studies have found that distinct domains of EFs develop fully at different stages (Davidson et al., 2006; Xu et al., 2013).

1.2.1.2. Neural Evidence

These rapid improvements in EFs during childhood have been shown to be underpinned by maturation of late-developing cortices, particularly the prefrontal cortex as well as parietal regions (Fiske & Holmboe, 2019; Shanmugan & Satterthwaite, 2016). Indeed, extensive changes in frontal and parietal cortical volume and functional connectivity over development have been shown to mediate EF improvements (Buss & Spencer, 2018; Tamnes et al., 2010).

1.2.2. Importance of early cognitive control

Childhood cognitive control, in particular, has been found to predict cognitive control later in life (Berthelsen et al., 2017). EF employment becomes even more crucial in periods after childhood. For example, let us focus on adolescence where there is a peak of mental health problems (Costello et al., 2011). With rising social pressure and onset of puberty, adolescence is a period of heightened vulnerabilities to experience socio-affective problems such as depression and anxiety (Bathelt et al., 2021). Mental health problems such as depression and anxiety are characterised by increased levels of rumination and worry (Gustavson et al., 2018; Hsu et al., 2015). Poorer attentional control could lead to individuals being more vulnerable to such dysfunctional cognitive styles (Hsu et al., 2015). Indeed, abnormal attentional control and emotion regulation has been demonstrated to play a significant role in vulnerability to depression and anxiety (Gustavson et al., 2018; Hsu et al., 2015). Tackling these EFs may be crucial to improving emotional wellbeing. Indeed, interventions based on working memory have shown promise in improving depression and anxiety in both clinical and non-clinical adolescent populations (Beloe & Derakshan, 2020; Schweizer et al., 2013). Strikingly, improvements in depression were found to be modulated by greater FPN activity, a network implicated in both EFs and also emotional control specifically (Schweizer et al., 2013). More directly, another paper found that children with impulsivity problems were more likely to have anxiety and emotional problems in adolescence (Berthelsen et al., 2017). These problems are pervasive into adulthood, with childhood executive functions shown to be an important predictor of later mental wellbeing (Moffitt et al., 2011). This highlights the important role that early cognitive control can play in the trajectory of an individual’s wellbeing.

1.2.3. Summary

Cognitive control develops rapidly in childhood supporting more complex EFs developing in adolescence. The trajectory of development differs between the EFs and is mirrored by maturation of frontal cortices. Entering adolescence, a period that confers risk, childhood cognitive control becomes even more so relevant and crucial in mitigating these poorer outcomes through better emotional regulation and attentional control.

1.3. Executive Function Interventions

Given the role childhood cognitive control has in predicting later life outcomes, interventions have focused their efforts in boosting it (Wass et al., 2012). In the previous section, we observed how earlier EF abilities are associated with later EF abilities (Berthelsen et al., 2017) as well as mental health (Bathelt et al., 2021). For instance, this suggests that although mental health problems peak in adolescence, vulnerabilities for these problems can be identified in childhood (Berthelsen et al., 2017; Moffitt et al., 2011). This reinforces the need for interventions to prevent later mental health problems by tackling potential EF dysfunction in childhood (Heckman, 2006). Additionally, it could be argued that childhood may be a critical period, serving as a window of opportunity to boost cognitive control. As described in the previous sections, neural substrates that underlie EFs undergo maturation in childhood (Diamond, 2015; Thompson & Steinbeis, 2020). Therefore, this is a particularly important period of time where cognitive control may be especially malleable.

1.3.1. Focus of current interventions

Like pharmacological interventions, cognitive control interventions typically are administered for a number of fixed sessions. In cognitive control interventions, typically a core mechanism is targeted through training (e.g. working memory trained using a standard n-back task). Control groups are usually either a passive control group or active control group who participate in a similar training condition without the 'active' training component (Thiese, 2014). We note, however, the difficulty in pinpointing 'active' ingredients of psychological interventions (Sebastian et al., 2021). With cognitive control training, typically the active component selected is an EF that theoretically operates as a mechanism of interest (i.e. changes in EF lead to changes in other domains). A majority of the intervention literature has focused on working memory as a core mechanism for training (Kassai et al., 2019). In such interventions (typically training children on a memory span task), pre-post improvements in working memory and other domains (such as fluid intelligence) are measured (Jaeggi et al., 2008; Judd & Klingberg, 2021; Klingberg, 2005; Spencer-Smith & Klingberg, 2017). While these interventions have been successful at improving the targeted mechanism itself, transfer to other domains have been more difficult to produce (Sala & Gobet, 2017). This suggests that mere correlations between training mechanism and outcome variables are insufficient (Moreau & Conway, 2014). For instance, in the context of working memory training, while training improves working span, it may not necessarily tap into a mechanism that may generally be involved in manipulation of information in all contexts (Thorell et al., 2009; Thorndike & Woodworth, 1901; Unsworth & Engle, 2005)**.** Therefore, it is necessary for training to employ a shared mechanism that may generally underlie EF. More discussion on lack of far-transfer has been provided in Section 1.3.3.1. and 1.3.4.

1.3.2. Inhibition-based interventions

As mentioned above, inhibition has long been considered to be at the core of cognitive and behavioural control (Aron, 2007). Indeed, studies examining multiple measurements of executive function in middle childhood have consistently yielded factor loadings of inhibition (Messer et al., 2018, St Clair & Gathercole, 2006, Wu et al., 2011, Hartun et al., 2020). Despite this, working memory and shifting have received most attention in the training literature as potential candidate mechanisms. Part of this could be attributed to earlier unsuccessful attempts leading to the premature conclusion that inhibition is too automatic a process to be trained (J. R. Cohen & Poldrack, 2008). Arguably, inhibition may be highly relevant to a wide set of processes including response selection, context monitoring and attentional control (Bari et al., 2020; Chatham et al., 2012; Mackie et al., 2013; Traut, Chevalier, et al., 2021; Wodka et al., 2007) as well as being core to clinically relevant behaviours such as ADHD and OCD (Blair & Razza, 2007; Mar et al., 2022; Wodka et al., 2007). More recently, training interventions employing inhibition have shown some promise and success (Berkman et al., 2014; Biggs et al., 2015; Delalande et al., 2020; Verbruggen et al., 2013; Zhang et al., 2019; Zhao et al., 2015). Specifically, patterns of far-transfer to other domains have been promising (Berkman et al., 2014). In particular, a recent adult study found that participants who had trained inhibition compared to a control group exhibited neural activation patterns indicative of a shift from reactive to proactive cognitive control (Berkman et al., 2014). This is particularly relevant as it may point to potential of far-transfer to other domains of cognitive control (i.e. not limited to inhibition solely).

1.3.2.1. Inhibition vs Context Monitoring

Arguably the ability to inhibit unwanted thoughts or actions depends on monitoring the environment for contextual cues that indicate the need to change action (Chatham et al., 2012; Dodds, Morein-Zamir, & Robbins, 2011; Hampshire et al., 2010). Typically, context monitoring is differentiated from inhibition based on the response that is required (e.g., requiring a double key press instead of inhibition in response to signal). In line with this theory, the neural and behavioural signatures underlying response inhibition were demonstrated to track monitoring demands more closely than motoric-stopping demands (Chatham et al., 2012). Additionally, context monitoring accuracy rather than stopping accuracy was shown to predict inhibition performance as well as right inferior gyrus (rIFG) activation that may underlie inhibition (Chatham et al., 2012). According to this account, inhibition can be subsumed by a more general process of action selection (i.e. selecting between initiation and inhibition of action).

In support of this hypothesis, a recent developmental paper found that while training either stopping an ongoing action or monitoring improved response inhibition, children who had practised monitoring outperformed the inhibition group (Chevalier et al., 2014). However, some potential methodological issues confound these findings. Therefore, a thorough investigation of context monitoring training may be necessary. Further, it has been argued that any infrequent stimulus (as is the case in virtually all studies arguing for a context monitoring account) require some form of inhibition (Aron et al., 2014). The literature on Pavlovian response biases, where appetitive cues are inherently associated with Go responses and aversive cues with No-Go or Stop responses (Guitart-Masip et al., 2011), suggests that approach and avoidance (i.e. inhibition) are underpinned by fundamentally different processes.

In sum, there remains substantial controversy over core processes of cognitive control. This controversy finds itself also in the developmental literature, where standard views of the primacy of response inhibition in cognitive control (Diamond, 2002) contrast with more recent accounts advocating for a core role of context monitoring (Winter & Sheridan, 2014; Chevalier et al., 2014). Given the importance of understanding the core processes of cognitive control in order to tailor interventions to foster this crucial skill early in life, causal evidence is needed. Chapter 3 will examine the malleability of these subprocesses of cognitive control (i.e. inhibition and context monitoring) to clarify which may be more beneficial in the context of training.

1.3.3. Limitations of current interventions

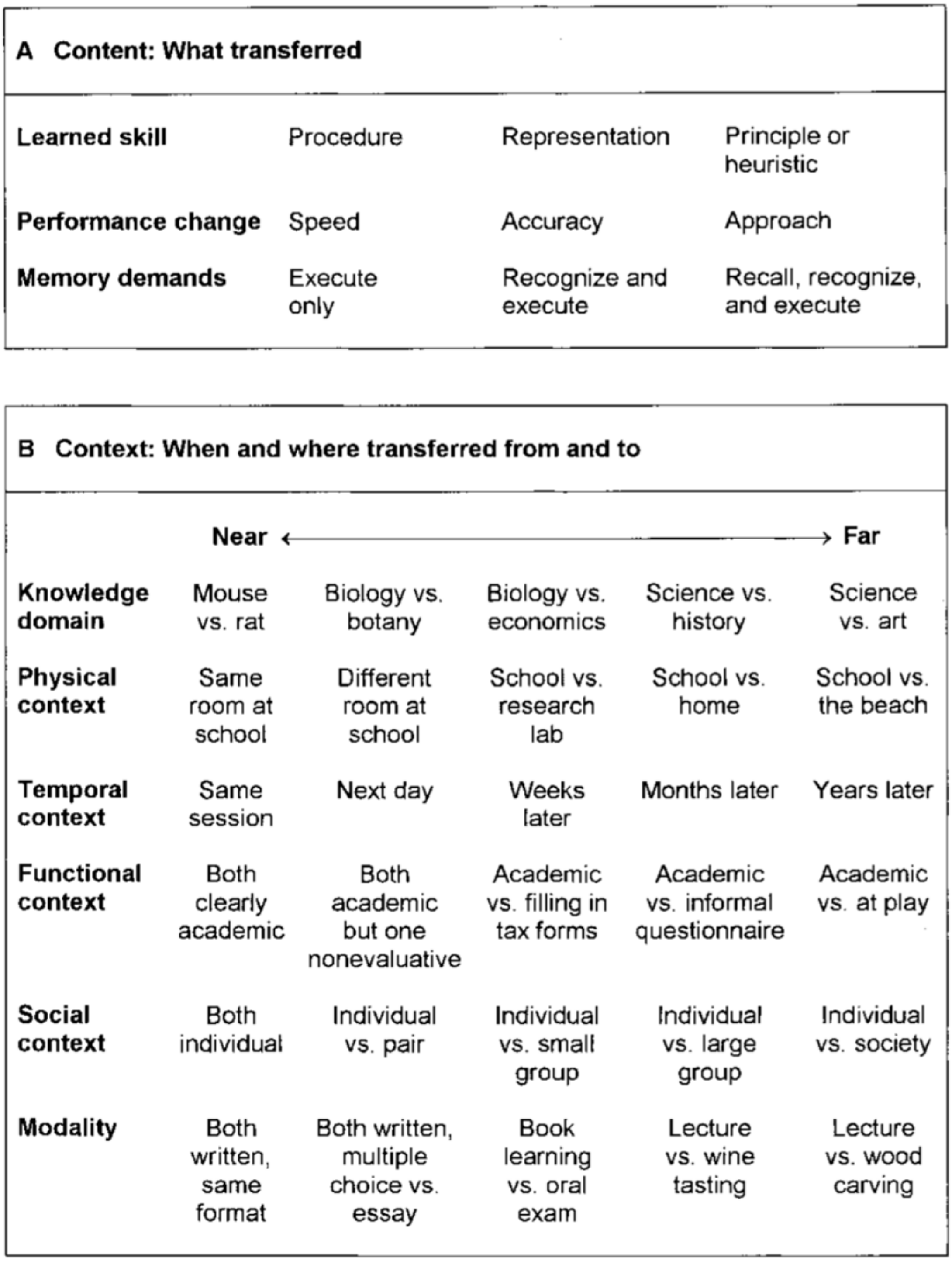
1.3.3.1. Near- and far-transfer

Overall, findings from intervention studies to date remain mixed (Diamond & Ling, 2016; Smid et al., 2020). Specifically, training studies have been successful at producing near-transfer (i.e. improvements within the same domain). However, interventions have been less successful in producing transfer to other, so-called far domains. Far-transfer can be conceptualised in a few different ways (Figure 1-2). It could refer to whether training one domain results in transfer in another domain. In another definition, it could refer to whether training a skill in a specific context (e.g. laboratory, computer-based) can result in improvements in that skill in another context (e.g. real-world). An in-depth review of these different conceptualisations demonstrate the considerations for training studies in defining far-transfer (Barnett &

Ceci, 2002). Specifically, with cognitive control training we would expect transfer to other EFs other than the target EF trained (i.e. transfer to inhibition and shifting through working memory training). This is rooted in the unity and diversity theory where there is shared commonality between the EFs (Miyake et al., 2000). Surprisingly, a paper found that neither inhibition nor shifting training produced convincing far-transfer effects to the untrained EF (Podlesek et al., 2021). Similarly, we may also expect transfer to other domains of wellbeing (i.e. economic and social functioning, mental health) given how strongly cognitive control operates as a predictor (Moffitt et al., 2011). Therefore, improvements in cognitive control should translate to improvements in wellbeing.

Surprisingly, the literature suggests transfer to other domains through cognitive control training is poor (Diamond & Ling, 2016; Sala & Gobet, 2017). For instance, there are well-established links between working memory and fluid intelligence so we may expect improvements in fluid intelligence (Jarrold & Bayliss, 2008). Counter to this, a meta-analysis showed that training interventions based on a working memory led only to improvements in working memory (Sala & Gobet, 2017). Overall, the evidence suggests producing transfer into non-EF domains has been difficult (Diamond & Ling, 2016; Holmes et al., 2019; Sala & Gobet, 2017). Perhaps, as discussed this may be due to interventions targeting a specific task-related function (e.g. increasing reaction times) rather than targeting a shared mechanism that may generally underlie EFs (Kubota et al., 2020). From this perspective, training inhibition may provide some promise given its relevance to attentional processes, but we note the mixed evidence on far-transfer through inhibition training like other EF training interventions (Berkman et al., 2014; Podlesek et al., 2021). More reasons for these mixed intervention findings have been discussed in Section 1.3.4.

We note that far-transfer to other domains is crucial as it is the core purpose of cognitive control interventions. We want to boost cognitive control to mainly improve positive outcomes associated with it. Therefore, near-transfer alone is not sufficient. Training cognitive control is an effortful endeavour that is taxing on children, teachers and schools. Therefore, it is important that we are able to optimise training interventions before implementing it as part of a normal curriculum.



A Content: What transferred

Learned skill	Procedure	Representation	Principle or heuristic
Performance change	Speed	Accuracy	Approach
Memory demands	Execute only	Recognize and execute	Recall, recognize, and execute

B Context: When and where transferred from and to

	Near ←				→ **Far**
Knowledge domain	Mouse vs. rat	Biology vs. botany	Biology vs. economics	Science vs. history	Science vs. art
Physical context	Same room at school	Different room at school	School vs. research lab	School vs. home	School vs. the beach
Temporal context	Same session	Next day	Weeks later	Months later	Years later
Functional context	Both clearly academic	Both academic but one nonevaluative	Academic vs. filling in tax forms	Academic vs. informal questionnaire	Academic vs. at play
Social context	Both individual	Individual vs. pair	Individual vs. small group	Individual vs. large group	Individual vs. society
Modality	Both written, same format	Both written, multiple choice vs. essay	Book learning vs. oral exam	Lecture vs. wine tasting	Lecture vs. wood carving

Figure 1-2. Taxonomy and levels of far-transfer (Barnett & Ceci, 2002).

1.3.3.2. Maintenance of training effects

Like with the importance of far-transfer effects, a similar reasoning applies with maintenance. Children, teachers and schools have limited resources. Therefore, it is unplausible for training to be administered frequently. Instead, we need to ensure that training administered leads not just to changes in the short-term but also long-term. Short-lasting training improvements may render non-beneficial and may lead to poor transfer effects (i.e. children unable to utilise improved EFs in other domains). Short-lived changes may reflect poor engagement and attention from children which may led to functions not being genuinely improved (Diamond & Ling, 2016; Nguyen et al., 2019)19). Indeed, although maintenance of training effects has generally been mixed in the literature, some adaptive designs have shown promise in sustaining training improvements (Holmes et al., 2009).

1.3.4. Reasons for heterogeneity of intervention success

Overall, the evidence on the success of training interventions is mixed. this suggests that intervention success is heterogenous. In particular, transfer to far domains and maintenance have been inconsistently reported. There are a couple of reasons that may explain this heterogeneity: non-malleability of cognitive control, training design and individual differences.

1.3.4.1. Non-malleability of cognitive control

First, we do need to consider that perhaps cognitive control is not malleable through experimental training. This suggests that any observed near-transfer effects are simply practice effects. This may explain the lack of far-transfer effects or maintenance (i.e. EFs not genuinely improved so does not lead to changes/benefits in other domains or in the long-term).

One contradiction here, however, is that cognitive control should be incredibly malleable in childhood, given the maturation of frontal areas during childhood that subserve them (Davidson et al., 2006; Fiske & Holmboe, 2019; Garon et al., 2014) Alternatively, it could be the case that while near-transfer can be genuinely improved, the specificity of the training (i.e. context, domain) means that EFs are only improved specifically in the context of the training environment. Therefore, children are unable to utilise this and apply them. This also explains why far-transfer to other domains such as mental health are rarely seen as real-world changes in cognitive control do not occur – only changes in task-specific domain occur. This may explain why despite strong cross-sectional and longitudinal links between cognitive control and better life outcomes, transfer into these outcomes are rarely seen (Koster et al., 2017; Sala & Gobet, 2017).

1.3.4.2. Design-related issues with training interventions

One issue that could contribute to inconsistent training outcomes may be that current training designs are unsuitable for children. Engagement is key in training designs and plays a role in the benefits children are able to reap (Smid et al., 2020). Engaging cognitive control is effortful therefore, children may simply not actively engage with training tasks explaining poor training changes (Botvinick & Braver, 2015). In a developmental population, in particular, having a gamified training design could be helpful in boosting engagement. For example, a gamified design could help retain high levels of motivation and engagement. Indeed, previous research has shown better training success in children with gamified designs (Smid et al., 2020). Strikingly, motivation has been found to be moderating factor of training effectiveness, with one study showing that engagement was crucial in producing and maintaining training improvements (Johann & Karbach, 2020).

1.3.4.3. Individual differences

Individual differences play a massive role in determining benefits children can reap from training interventions. In particular, their baseline abilities play an important role where specifically children with poorer cognitive control abilities have been found to gain the most from training interventions (i.e. compensation effect; Karbach & Kray, 2009; Karbach & Unger, 2014; Traut, Guild, et al., 2021).Therefore, ensuring that the difficulty of training is scaled to children's abilities may be crucial. This would ensure that training is challenging enough to keep children motivated and that they are able to reap benefits from the training, regardless of their baseline abilities. Ensuring that training is not too difficult will help minimise feelings of frustration that may lead to children giving up on training tasks. An additional benefit of having an adaptive design is that it helps minimise ceiling effects and children can continue to benefit from the training even as they get better (Karbach et al., 2015, 2017; Könen & Karbach, 2015).

Additionally, looking at individual differences may help shed light into mechanisms through which change occurs. In particular, it could help us understand the mechanism through which far-transfer or maintenance occurs. We could hypothesise that for far-transfer or maintenance to be observed, underlying changes in neural substrates would need to have occurred. By measuring a range of individual differences in brain-behaviour indices, we could probe at mechanisms that may underlie change and further understand individual differences predicting success. Chapter 5 takes this approach examining brain-behaviour individual differences predicting training success.

1.3.5. Summary

Childhood is an important period of time where cognitive control may be particularly malleable, serving as an opportunity for training interventions. Efforts have focused mainly on training cognitive control using memory and shifting as mechanisms. While inhibition has been trained less so, it may hold some promise. On the whole interventions have successfully produced near-transfer but less so in far-transfer domains. This may potentially be explained by individual differences and training design issues rather than the non-malleability of cognitive control. Chapters 4 and 5 build on this idea to evaluate the success of training cognitive control through a gold-standard design – examining far-transfer, maintenance and individual differences.

1.4. The role of effort in executive functions

In recent years, motivation has been argued to play a key role in how executive functions are used. This has led to a re-examination of EFs, less as competencies or abilities that change as a function of cortical maturation but more as resources that are deployed depending on context (Qu et al., 2013; Tarullo et al., 2018). It has been argued for instance that inhibition of responses or manipulation of information is cognitively effortful, requiring attention and resources (Botvinick & Braver, 2015). The use of EFs is thus highly sensitive to the value associated with the goal and to the effort costs associated with the action to obtain it (Sayalı & Badre, 2021; Shenhav et al., 2017). One prominent theory posits that the decision to exert effort may be based on cost-value of effort exertion (Shenhav et al., 2017). Specifically, given limited resources, individuals may compare the cost and value associated with effort exertion to decide if exertion of effort is worthwhile. Doing so allows for efficient exertion and allocation of effort, ensuring resources are not unnecessarily used and depleted (Shenhav et al., 2017).

Developmentally, children as young as 4-years have been documented to be sensitive to effort expenditure (Leonard et al., 2017). It is thus a distinct possibility that EF performance can at least in part be explained by motivation rather than abilities. Indeed, previous studies have shown that effort exertion explains performance, which in turn can explain task performance variability attributed to differences in ability (Foussias et al., 2014; Salamone et al., 2016; Umemoto & Holroyd, 2015; Westbrook et al., 2020). Given how sensitive children are to effort, reward also exerts a prominent influence on performance on EF tasks (Frömer et al., 2021). Consistent with observed neural signatures, adults have been shown to allocate more control on trials predicted to be more rewarding (Frömer et al., 2021). Similarly, children as young as 4-years old have been found to perform significantly better on EF tasks when they were informed about rewards they would receive or provided with reward-related feedback (Qu et al., 2013; Tarullo et al., 2018). There have been reported developmental differences in reward sensitivity that determine EF performance which can be explained by continued maturation of corticostriatal connectivity (Insel et al., 2017). In turn, this could explain any observed age differences in cognitive control (Davidson et al., 2006).

However, the evidence on the development of such effort avoidance in a developmental population is mixed. While one paper found that only older children were able to avoid effort (Niebaum et al., 2021), another study found that children of all ages devalued effort (Chevalier, 2018). However, this could potentially be explained by the type of tasks employed with varying levels of saliency in effort cues.

In Chapter 6, I aim to clarify this by probing at effort-related decision making in children using different paradigms.

1.4.1. Summary

Using cognitive control is effortful. Therefore, performance on cognitive control tasks could be partially confounded by lack of engagement or motivation. As a first step, Chapter 6 clarifies effort-related decision making in children.

1.5. Overview of experimental chapters

This chapter provided an overview of the role cognitive control plays in fulfilling our daily and long-term goals. I examined the overlap and separable nature of EFs as evidenced by behavioural and neural data. Additionally, a review on the effectiveness of current cognitive control interventions was provided. The potential methodological shortcomings of current interventions may explain its poor outcomes. Given this confound, we are unable to draw accurate conclusions about the plasticity of cognitive control through training interventions. Finally, I discuss the possibility that EFs need to be examined from a valuation-based framework which may provide insight and implications for interventions.

This thesis aimed to address limitations in the current literature to investigate in a developmental sample: the neural substrates of EFs, the efficacy of training interventions (i.e comparing two different mechanisms of cognitive control, examining extent of transfer) and effort-related decision making. As a note, Chapters 2, 4 and 5 involve analyses of the same dataset.

Research questions:

1. What are the neural substrates underlying executive functions?

Chapter 2 uses a multi-measurement approach (*N* = 141, *M* = 8.97 years) to create latent factors of EFs (i.e. inhibition, memory and shifting) to combat any task-related impurity issues. While age-dependent neural correlates were identified for memory abilities, age-independent neural correlates were identified for shifting abilities. No neural correlates were identified for inhibition abilities helping to clarify some of the contradictions observed in the literature.

2. Which mechanism is more effective in training cognitive control?

Chapter 3 examines which mechanism of cognitive control may be more effective in producing improvements. Specifically, the mechanisms of inhibition and context monitoring were compared (*N* = 60, *M* = 8.25 years). I found that while all groups improved on their targeted functions, training through inhibition exhibited the most promise with transfer to proactive control observed. These data support a privileged role of inhibition in cognitive control during childhood. Based on findings from this chapter, inhibition was chosen as the mechanism for interest for Chapters 4 and 5.

3. What is the extent of transfer to other EFs through cognitive control training (employing inhibition)?

Chapter 4 examines if a gold-standard cognitive control training design employing inhibition (*N* = 235, *M* = 8.97 years) was effective in producing transfer to the other EFs. Multi-measurements of each function are employed to create latent factors to increase reliability. I found that our training was effective in improving general strategic slowing as indicated by increases in reaction times in the experimental group.

4. What is the extent of transfer to a real-world outcome through cognitive control training (employing inhibition)?

Chapter 5 investigates whether transfer to a real-world outcome (i.e. attentional control reported by parents) could be achieved through our gold-standard cognitive control training (*N* = 235, *M* = 8.97 years). I reported improvements in attentional control scores in the experimental group, although this effect was not sustained. Crucially, baseline and changes in functional activity in the inhibition network predicted training-related improvements in attentional control scores. This provides a multi-level account of processes and individual differences underpinning successful transfer of cognitive training to real-world outcomes.

5. How do children make effort-related decisions?

Chapter 6 investigates effort-related decision making in a developmental population (*N* = 79, *M* = 7.91 years). I reported that, while overall children demonstrated no implicit behavioural preference for low effort tasks, older children stated a preference for low effort tasks and all children discounted effort. Further, implicit preference was linked to children's metacognitive insight into how well they could perform effortful tasks. These findings strongly suggest that while children are clearly sensitive to manipulations of cognitive effort, whether and when they use this information to guide their decisions to engage in effortful tasks depends strongly on the extent to which effortful features are made salient to them.

Chapter 2. Structural basis of executive functions in childhood.

Part of Chapter 2 has been written in preparation for publication. Ganesan, K., Smid, C., Cañigueral, R., Thompson, A., & Steinbeis, N. (in prep) Structural basis of executive functions in childhood.

2.1. Abstract

Executive functions are comprised of a subset of cognitive processes typically classified into inhibition, working memory and shifting. Together, these processes support flexible and goal-directed behaviour and are crucial for both current and later-life outcomes. A large body of literature has identified distinct brain regions that are critical to performing each of these functions. These findings are however predicated on a piecemeal and single-task approach and it is therefore unclear to what extent these associations reflect task-specific features or genuine executive function constructs. Here, in a large developmental sample of children (*N* = 141; age 6-13 years), we administered a battery of 9 executive function tasks, derived latent factors of inhibition, memory, and shifting, and examined their associations with whole-brain cortical thickness. Given the wide age range, we investigated both age-dependent and -independent effects. While we found no significant brain clusters associated with inhibition, we identified age-dependent associations between working memory and cortical thickness of right prefrontal, superior frontal and medial temporal lobe, and age-independent associations between shifting and cortical thickness of bilateral frontal and occipital lobes and left medial and anterior temporal lobes. We discuss these findings in relation to theories of executive functions and their development.

2.2. Introduction

Accomplishing everyday and long-term goals requires control of thoughts and actions. Executive functions (EFs) describe a cluster of cognitive processes that enable such goal-directed behaviours (Botvinick & Braver, 2015; Diamond, 2013). Specifically, three core EFs have been identified: stopping pre-potent responses and impulses (inhibition), manipulating and remembering goal-related information (working memory), and responding flexibly to changes in the environment (shifting). Impairments in executive functions have been associated with poor behavioural outcomes and clinically relevant behaviours of neurodevelopmental disorders such as ADHD and OCD (Mar et al., 2022; Wodka et al., 2007). Understanding the neural underpinnings of EFs during child development is therefore critical for diagnosis and treatment of clinical disorders characterised by EF deficits, as well as for devising interventions to support EFs in typically developing children (Auerbach, 2022).

A key question also termed the diversity-unity debate in the study of executive functions and its development is whether EFs are indeed separable constructs or whether they effectively represent different manifestations of the same underlying process (Fiske & Holmboe, 2019; Friedman & Miyake, 2017; Miyake et al., 2000; Miyake & Friedman, 2012; Niendam et al., 2012). Developmental studies suggest a unified structure of EFs in childhood, which supposedly emerges into more diverse and known subprocesses (Brydges et al., 2014; Wiebe et al., 2008, 2011). More recently neuroimaging has been suggested to be able to arbitrate between these distinct positions (Engelhardt et al., 2019; McKenna et al., 2017), with distinct brain regions supporting EF processes being taken as evidence in favour of diverse processes. To date a plethora of studies has examined the functional and structural underpinnings of EFs, finding distinct yet overlapping neural substrates that underlie EF functions (Collette et al., 2006; McKenna et al., 2017). Specifically, the bilateral frontal-parietal network (FPN), proposed to modulate general aspects of EF, has been found to underpin all three functions (Cole et al., 2013; McKenna et al., 2017). In contrast, different regions have been reported to distinctly underlie the three EFs (Aron, 2007; Bell & Fox, 1992; Buss et al., 2014; Fiske & Holmboe, 2019; McKenna et al., 2017; Tamnes et al., 2010). Some inconsistencies have been observed, for instance one meta-analysis found no distinct neural substrates to underpin inhibition, while individual studies (employing single measurements) have found inhibition to be underpinned distinctly by a range of occipital, parietal and frontal regions (He et al., 2021; McKenna et al., 2017; Saylik et al., 2022; Tamnes et al., 2010).

One particular issue in the measurement of EFs and their associations with brain structure or function is the fact that most studies employ single measures of executive functions (Snyder et al., 2015; Tamnes et al., 2010). It is well known that executive function tasks are rarely pure, in terms of capturing single sub-processes (Friedman & Banich, 2019; Zeynep Enkavi et al., 2019). For instance, in a stop signal task, while inhibition may be the core process involved in the performance of the task, working memory (i.e. remembering task instructions) and shifting abilities (i.e. alternating stop and go responses) may be necessary as well. Such task impurity implies that associated neural correlates may not purely represent any specific EF process, but presumably a combination of processes or indeed very specific task demands (Snyder et al., 2015). These issues may contribute to the inconsistency in neural correlates observed between studies (McKenna et al., 2017; Tamnes et al., 2010). Therefore, a multi-measurement approach may be necessary to identify the neural underpinnings of EF functions and to assess their relationship with one another.

Additionally, differentiation between age-dependent and age-independent neural substrates underlying EFs may be necessary. Research indicates that EFs emerge as early as infancy and undergo protracted development into early adulthood (Wiebe & Karbach, 2017). In particular, EFs mature rapidly in middle childhood, although the developmental progression of the three EF functions has been found to differ (Davidson et al., 2006; Fiske & Holmboe, 2019; Garon et al., 2014; Xu et al., 2013). Similarly, neural substrates that have been reported to underpin EFs undergo protracted development (Fiske & Holmboe, 2019; Shanmugan & Satterthwaite, 2016). Indeed, extensive changes in frontal and parietal cortical volume and functional connectivity over development have been shown to mediate EF improvements (Buss & Spencer, 2018; Tamnes et al., 2010). This suggests that in developmental populations in particular, it is necessary to differentiate between age-dependent and age-independent associations between EFs and neural substrates. Age-dependent associations may point to brain maturation over a developmental trajectory that mediate gains in EFs. In contrast, age-independent associations may indicate crucial individual differences in cortical thickness that are associated with EF abilities.

This study uses a factor approach to measure EF functions, minimising task-specific variance in large cohort of children (*N* = 148) aged 6-13 years and relates performance to brain structure. With this, (i) we examined the relationship between cortical thickness and factors of executive function (i.e. inhibition, shifting, and memory) and assess whether these are shared or distinct; and (ii) whether these relationships were age-dependent (disappearing when age is controlled) or age-independent (remaining when age is controlled).

2.3. Materials and Methods

2.3.1. Participants

A total of 262 typically developing children were recruited for the study (6.03-13.31 years; *M* = 8.97 years, Females = 52.84%) from schools within Greater London in the United Kingdom (data collection started in May 2019 and ended in May 2021). The UCL ethics committee approved the study (Protocol number: 12271/001). In accordance with this, written consent was obtained from both parents and children after providing a description of the study. Ethnic composition of our sample was as follows: Asian = 14.65%; Black = 3.18%; Mixed/multiple ethnic groups = 17.20%; White = 64.33%; Other = 0.63%). There were no specific exclusion criteria, although a safety protocol was followed for the scanning session that excluded some children (e.g. metal in the body; claustrophobia). A successful anatomical scan was collected from a subset of 141 participants.

2.3.2. Executive Function Tasks

A total of 9 executive function tasks were collected, assessing different functions (i.e. inhibition, shifting, and working memory). Visual designs of these tasks have been shown in Supplementary Figures S1-8. For all tasks, participants were presented with practice trials before main trials were administered, where they had to attain a criterion threshold for accuracy. Additionally, comprehension questions were employed to ensure participants understood the rules for each task (e.g. ‘What button should you press if you see a bear on the screen?’). Rules were re-explained if participants answered incorrectly on any of the questions. The experimenter noted if the participant still failed to comprehend the task. All participants managed to pass these comprehension questions; therefore, no individual was excluded from the analysis.

2.3.2.1. Inhibition Tasks.

Stop-Signal Reaction Time Task. A measure of cognitive control was administered via a child-friendly version of the SSRT (Matzke et al., 2018). Ten practice trials were administered before 80 trials of the main task. Each trial started with the presentation of a fixation cross of 1250ms. During the task, participants were asked to press the left arrow key when seeing the ‘go’ signal (i.e. a honey pot) on the left side of the screen and the down arrow key when the signal appeared on the right side. On 25% of the trials (i.e. a ‘stop’ trial), a picture of bees was presented after the honey pot. This served as the ‘stop’ signal. The stop signal delay (SSD) started at 200ms, decreased by 50ms after a successful ‘stop’ trial, and increased by 50ms after an unsuccessful ‘stop’ trial. As a measure of inhibition, a mean SSRT was calculated using the integration method (Verbruggen et al., 2019). Several studies have validated the SSRT as a measure of response inhibition (Logan et al., 2014) and it is correlated with self-report measures of impulsive behaviours in young adults (Logan, 1997).

Flanker Inhibition. The participants completed a child-friendly version of the Eriksen Flanker inhibition task (Eriksen and Eriksen, 1974). Children were presented with a row of fish on the screen. They were required to focus on the fish in the centre (named Chloe) and indicate the direction in which it was swimming (i.e. left key response required when the fish was facing left; down key response required when the fish was facing right). Participants were told to ignore the direction other fish swim in and only indicate the direction Chloe swam in. On congruent trials, all fish faced the same direction. On incongruent trials, surrounding fish faced the opposite direction to Chloe. Fish were presented for 700ms before they disappeared. Participants were given a maximum of 2500ms to respond from stimulus onset. A total of 20 congruent trials and 20 incongruent trials were administered. This task was chosen because it is a child-friendly task for ages six years and up and has been validated in several studies (McDermott et al., 2007; Mullane et al., 2009). The difference in both reaction times and error rates between incongruent trials and congruent trials was calculated.

Stroop. Participants completed a child-friendly version of the Stroop task (Williams et al., 2007). The task was introduced as the ‘Farm Animal’ game, where they were told to match animals to their homes (e.g. dog to a kennel). They were presented with both auditory stimuli of an animal sound (e.g. ‘bark’, ‘meow’, ‘croak’ for a dog, cat, and frog, respectively) and visual stimuli of the animals. Crucially, participants were asked to match animals to where they live (e.g. frog to a pond). They were told to listen carefully to an auditory cue indicating the animal type (e.g. frog – ‘ribbit’) and not to pay attention to the visual cue of the animal presented on the screen. Trials lasted for 10000ms within which participants had to make a response. While audio stimuli was presented for 600ms, visual stimuli was presented until participants made a response (max of 1000ms). A blank screen with a ‘cross’ was presented between trials for 10000ms (ITI). On congruent trials, both auditory and visual cues matched (e.g. frog presented on screen and ‘ribbit’ tone played). On incongruent trials, auditory and visual cues did not match (i.e. dog presented on screen and ‘ribbit’ tone played). Participants completed 72 trials in total, with 36 congruent and 36 incongruent trials. The differences in both reaction times and error rates between incongruent trials and congruent trials were calculated.

2.3.2.2. Memory Tasks.

N-back. Both the 1-back and 2-back tasks were administered to measure working memory (Chen et al., 2008). The task was adapted to be child-friendly and introduced as the ‘Dino-Donut’ game, where participants were told that dinosaurs were lining up to eat some donuts. For the 1-back task, they were told to stop dinosaurs that tried to eat a donut twice in a row and to press the spacebar if they appeared consecutively to stop them. For the 2-back task, they were told that the dinosaurs became sneakier, and this time they should press the spacebar if the same dinosaur appeared two trials prior. Stimuli were shown for 500ms followed by a 1500ms Inter-Stimulus-Interval (ISI). Responses had to be made before the onset of the next stimulus presentation. Participants completed 80 trials in total, 40 for each n-back condition. A d-prime score based on hit rate and false alarm rate was calculated for both 1-back and 2-back tasks.

Corsi block-tapping task. Working memory span was assessed using the Corsi block-tapping task, which measures visuo-spatial working memory span with a higher value indicating a higher working memory span (Farrell Pagulayan et al., 2006). This task consisted of ‘Freddy the frog’ jumping between nine potential locations designed as lily pads. The participants followed the jumps by clicking on the lily pads in a forward sequence. Trials commenced with a count-down from three to one to alert participants to the start of a trial. Then the stimulus of the frog jumping was shown for 600ms for every jump. The ISI was fixed to 600ms. Participants completed three practice trials with feedback and there was a total of 14 main trials.

Initially, participants had to remember and click on two lily pads. The task employed an adaptive staircase design where the working memory load (i.e. number of lily pads to remember) increased by one when participants made two consecutive correct answers. The maximum working memory load attained was used as a working memory span measure.

2.3.2.3. Shifting Tasks.

Cognitive Flexibility. A child-friendly version of the cognitive flexibility task assessed participants' ability for rule switching across dimensions (using sound cues: ‘animal’ or ‘size’). If a sound cue of ‘animal’ was played, participants had to indicate if the animal was a cat or dog. If a sound cue of ‘size’ was played, participants had to indicate if the animal was big or small (Karbach & Kray, 2009). Participants had 10 seconds to respond before the trial timed out, during which the stimuli remained on the screen—responses made before 200ms after stimulus onset were not recorded. The inter-trial interval (ITI) was jittered and ranged from 1000ms to 1200ms. Stay trials were preceded by a trial with the same rule (e.g. deciding on the type of animal was presented twice in a row). During switch trials, the current trial was preceded by a trial in a different dimension (i.e., participants had to first respond to the size of the animal and then to the type of animal that is presented). Following a practice block, participants completed 40 trials (consisting of 28 stay trials and 12 switch trials). Participants completed 20 single-dimension trials in two blocks and 40 mixed trials in one block. The difference in reaction times between switch trials and stay trials was calculated.

Flanker Shifting. The participants completed a child-friendly version of the Eriksen Flanker shifting task (Karbach & Kray, 2009). Children were presented with a row of fish on the screen. They were told that all the fish swim in the same direction. However, that two colours of fish would appear: orange and purple fish. When orange fish were presented, they were instructed to indicate the direction in which the fish swam (i.e. left key response required when the fish faced left; down key response required when the fish faced right). When purple fish were presented, they were instructed to indicate the opposite direction in which the fish swam (i.e. left key response required when the fish was facing right; down key response required when the fish was facing left). Fish were presented for 700ms before they disappeared. Participants were given a maximum of 2500ms to respond from stimulus onset. Stay trials were defined as those where the rule for the previous trial was the same as the current trial (i.e. purple trial following a purple trial; orange trial following an orange trial). Switch trials were defined as those where a rule change has occurred (i.e. purple trial following an orange trial; orange trial following a purple trial). Based on this, there were 28 stay trials and 12 switch trials. The difference in both reaction times and error rates between switch trials and stay trials was calculated.

2.3.2.4. Complex EF Tasks.

AX-CPT. Reactive and proactive control were measured using a child-friendly version of the AX-CPT paradigm (Chatham et al., 2009). The task was introduced as the Fruit Island game. An ‘A’ or ‘B’ cue (i.e. dog or cat) was presented in the middle of the screen for 500ms, followed by an inter-stimulus interval of 750ms and then a probe ‘X’ or ‘Y’ (orange or apple) during which participants had to make their response. Participants were instructed to press the left key whenever an ‘X’ followed an ‘A’ (i.e. AX trials) and to press the down arrow key for all other cue-probe combinations. Importantly, they were instructed to only respond once the probe had been presented and were alerted of this if they made a response before the probe was presented. Participants had a maximum of 6000ms to make a response. Responses were followed by an inter-trial interval of 1500ms. The proportions of the trial types were based on previous studies (Chatham et al., 2009; Richmond et al., 2015) where 40% of trials were AX trials. All other trials (i.e. AY, BX, BY trials) were presented 20% each. Trials were presented randomly. Ten practice trials were administered where feedback was provided, followed by 60 main trials.

2.3.3. Brain Structure data acquisition.

As part of a battery, a structural scan was obtained with a Siemens 3.0 Tesla Prisma scanner located at the Birkbeck-UCL Centre for Neuroimaging (BUCNI) equipped with a standard whole-head coil. For this, magnetisation-prepared rapid gradient-echo sequence (MP-Rage) was used (TR = 2.30s TE = 2.98ms, flip angle = 8°, slices = 1 x 1 x 1 mm^3 voxels, field of view 256 x 256). Children were told to keep their heads as still as possible to reduce head motion, and foam inserts were placed between the head and the head coil. Visual stimuli were projected onto a screen in the magnet bore that could be viewed through a mirror attached to the head coil. Children watched cartoons without auditory stimuli during the acquisition.

2.4.1. Statistical Analysis

2.4.1.1. Executive Function factors.

Outliers were removed from behavioural executive function measures. Datapoints falling two standard deviations below or above the mean were excluded. Then, a confirmatory factor analysis (CFA) was performed using lavaan in Rstudio to create latent factors of EFs (Rosseel, 2012). FIML was used to deal with any missing data in the dataset. Multiple models were fit, however, the model failed to converge for most models, with some of them displaying negative variances suggesting that models were mis-specified. Only two models converged showing good fits (CFI > 1.00; TLI > 1.00): a model with a single factor encompassing all tasks and a model with three sub-factors of inhibition, shifting, and memory. There were no significant differences in model fits ($\Delta\chi^2$ (3) = 1.69, p = .638). For our hypothesis, as we were aiming to look at the three executive functions separately, we chose the model with the three sub-factors of executive functions (Figure 2-1). Values for each individual were extracted from this for further analysis (where bigger values indicated better executive function abilities).

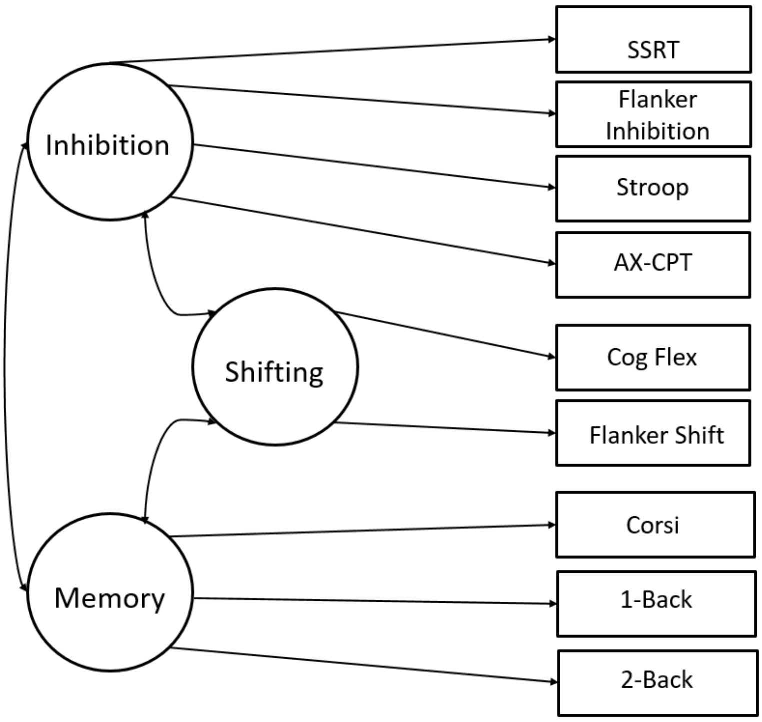


Figure 2-1. Loading of executive function tasks on inhibition, shifting and memory factors.

2.4.1.2. Cortical thickness.

After converting the Dicom files to Nifti using dcm2niix, structural MRI images were processed with FreeSurfer (Version 6.0.0; http://surfer.nmr.mgh.harvard.ed; Fischl et al., 2002) to label and segment cortex and white matter. Then, all scans were manually visually inspected for quality, and if necessary, segmentation was manually corrected in FreeSurfer. Four independent inspectors conducted these checks, and one final inspector performed a final inspection of all scans. After corrections, scans were re-segmented using FreeSurfer. If the quality of scans was inadequate, these were excluded from the final analysis. Based on this, data was available from 141 participants. After pre-processing, sulcal and gyral features across individual subjects were aligned by morphing each subject's brain to an average spherical representation that accurately matches cortical thickness measurements across participants while minimizing metric distortion. A 10mm Gaussian smoothing kernel was applied to data to reduce measurement noise but preserve the capacity for anatomical localizations (Bernhardt, Klimecki, et al., 2014; Lerch & Evans, 2005). Cortical thickness data were analyzed using the SurfStat toolbox for Matlab (https://www.math.mcgill.ca/keith/surfstat; Worsley et al., 2009). Linear regression models were used to assess the effects of age and executive function factors on cortical thickness at each vertex. Findings from the surface-based analyses were controlled for multiple comparisons using random field theory (Bernhardt, Klimecki, et al., 2014; Bernhardt, Smallwood, et al., 2014; Steinbeis et al., 2012; Worsley et al., 2009). This reduced the chance of reporting a family-wise error (FWE). The threshold for significance was set to a stringent p <0.025. The Desikan-Killiany atlas (Desikan et al., 2006) was used to label any observed significant cortical thickness correlates.

2.4. Results

2.4.1. Correlations with age

All three executive function factors were correlated with age (r > .42, p <.001; Table 2-1). Specifically, age was associated with better executive function abilities.

Table 2-1. Correlations between age and EF abilities.

Measures	Age	Inhibition	Shifting
Age	1.00	-	-
Inhibition	0.42	1.00	-
Shifting	0.52	0.57	1.00
Memory	0.52	0.85	0.90

Note: All observed correlations were significant at $p < .001$.

2.4.2. Cortical thickness and age

Cortical thickness in ten clusters were significantly associated with age. Only one of these associations was positive (i.e. cortical thickness; Figure 2-2a), with all other nine associations were negative (i.e. cortical thinness; Figure 2-2b). For more details on these regions, see Supplemental Materials-2.

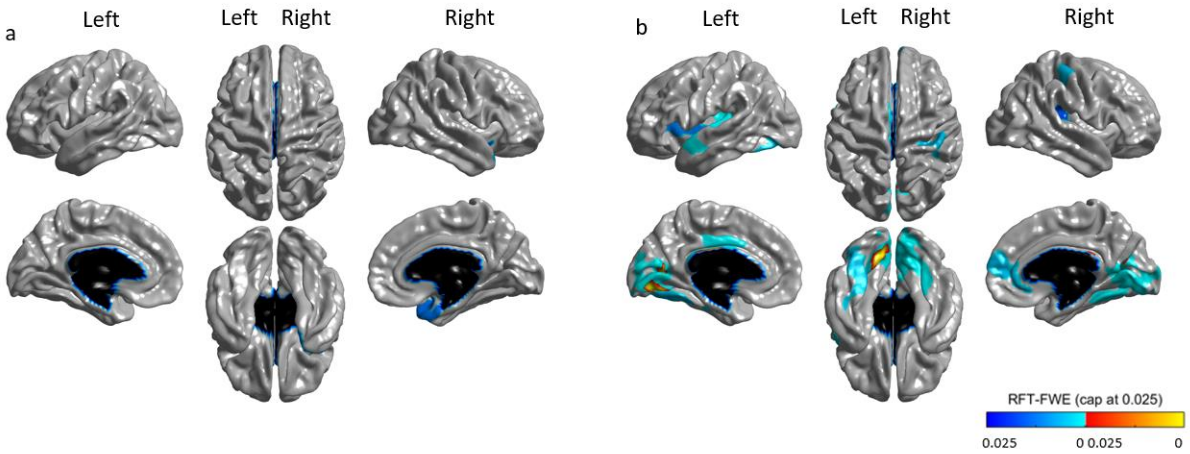


Figure 2-2. (a) Significant association between cortical thickness in one cluster in the right temporal lobe was found. (b) Significant associations between cortical thinning in nine clusters in bilateral temporal lobes, and right frontal lobe were observed. *Note: RFT-FWE refers to Random Field Theory-based familywise error (FWE) correction where a stringent threshold of p = .025 was set. Blue values indicate significant clusters while red/yellow values indicate significant peaks.*

2.4.3. Inhibition and cortical thickness

No clusters were found to be associated with inhibition abilities both before and after age was added in as a covariate.

2.4.4. Memory and cortical thickness

Memory was positively associated with cortical thickness of 2 clusters (Figure 2-3). The first cluster was observed in the right medial temporal lobe consisting of the entorhinal cortex, fusiform gyrus, insular cortex, superior temporal gyrus, and temporal pole. The second cluster was observed in the right lateral frontal lobe, consisting of the superior frontal gyrus and precentral gyrus. However, we note that these associations disappeared after age was added in as a covariate.

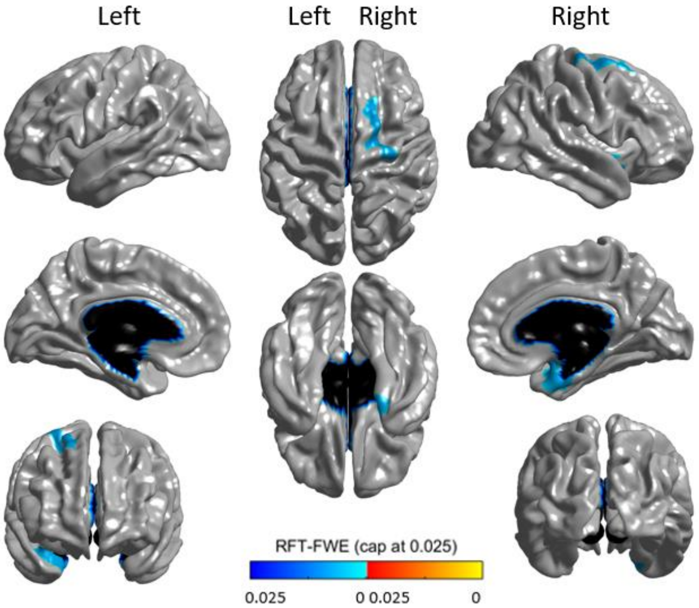


Figure 2-3. Significant associations between cortical thickness in two clusters in the right frontal and medial temporal lobes and memory were found. Notably, these associations did not survive after age was controlled for. *Note: RFT-FWE refers to Random Field Theory-based familywise error (FWE) correction where a stringent threshold of p = .025 was set. Blue values indicate significant clusters while red/yellow values indicate significant peaks.*

2.4.5. Shifting and cortical thickness

Shifting was positively associated with cortical thickness of three clusters. All three clusters were located in bilateral frontal lobes: left precentral gyrus, right superior frontal gyrus, right caudal middle frontal gyrus, right precentral gyrus, and right paracentral gyrus (Figure 2-4a). Adding age in as a covariate uncovered additional associations. Specifically, shifting abilities were positively associated with thickness of eight clusters (Figure 2-4b). Four of these clusters were located in the left hemisphere. The first cluster was located in the left frontal lobe consisting of the precentral and postcentral gyri. The other three clusters were located in the left occipito-temporal lobe consisting of the lateral occipital, fusiform, lingual, inferior temporal and middle temporal gyri. The other four clusters were located in the right hemispheres. Two of these were located in the right frontal lobe and cingulate cortex consisting of the caudal anterior cingulate, medial orbitofrontal cortex, rostral anterior cingulate, rostral middle frontal gyrus, superior frontal gyrus, pars opercularis and precentral gyrus. The next cluster was observed in the right frontoparietal and cingulate cortex consisting of the precentral, paracentral, postcentral, superior frontal gyri and the precuneus and posterior cingulate cortex. The final cluster was observed in the right occipital lobe consisting of the inferior occipital and lateral occipital gyri.

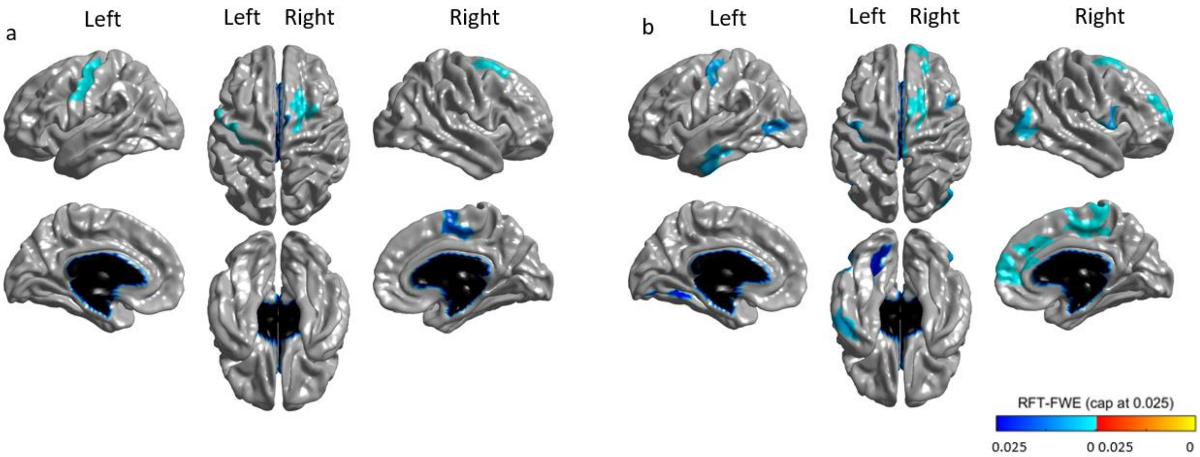


Figure 2-4. (a) Significant associations between cortical thickness in three clusters in the bilateral frontal lobe were observed. (b) After controlling for age, significant associations between cortical thickness in bilateral frontal and occipital lobes and left medial and anterior temporal lobes were observed. *Note: RFT-FWE refers to Random Field Theory-based familywise error (FWE) correction where a stringent threshold of p = .025 was set. Blue values indicate significant clusters while red/yellow values indicate significant peaks.*

2.5. Discussion

This study aimed to use a multi-measurement approach to capture constructs of EFs. Using this method, we examined neural correlates of EFs. Further, given the developmental trajectory of both EF and neural maturation, we examined how these brain-behaviour associations changed. Age-dependent neural correlates of working memory were identified. In contrast, age-independent neural correlates of shifting abilities were identified suggesting that individual differences in cortical thickness may be an important predictor for shifting abilities in our developmental sample.

Using a multi-measurement approach, we created subfactors of EFs. This led to factors of inhibition, memory and shifting abilities. In line with previous literature, we we identified a 3-factor structure that fit our data, representing functions of inhibition, memory and shifting abilities (Völter et al., 2022; although see Messer et al., 2018). Using this method, we were able to isolate individual EFs (inhibition, memory, shifting). This allowed us to examine true neural correlates of the three functions rather than any associations being potentially confounded by overlap between EFs or task-related variance. In line with previous research, age was significantly correlated with all three executive functions (Garon et al., 2014). This helped serve as a validation for our factors of EFs.

No clusters were found to be associated with our inhibition factor. This may help reconcile inconsistent neural substrates found to underpin inhibition (He et al., 2021; McKenna et al., 2017; Saylik et al., 2022; Tamnes et al., 2010). Through our factor analysis, we isolated a factor of inhibition (i.e. no overlap with other executive functions). This suggests that any previously identified neural correlates found to specifically underlie inhibition may have represented task-specific elements or other EFs rather than inhibition per se. Indeed, a meta-analysis found that activation in regions associated with inhibition, completely overlapped with common executive function areas (McKenna et al., 2017). Our observations are in line with this, where no correlates of our inhibition factor were identified. This could point to inhibition potentially being a general processing ability rather than a specific function. Inhibition has been found to develop towards the end of the first year (Holmboe et al., 2018), and then to rapidly develop during toddler years (Best et al., 2009; Best & Miller, 2010; Friedman et al., 2011; Garon et al., 2008, 2014). Therefore, inhibition abilities may simply represent a generalised processing ability to support simpler goals in younger children with distinct executive processes developing in later childhood (Davidson et al., 2006; Friedman et al., 2008, 2011; Friedman & Miyake, 2017; Miyake & Friedman, 2012).

Memory abilities were found to be associated with cortical thickness of clusters in the right prefrontal, superior frontal and medial temporal lobe. This is supported by the literature suggesting the entorhinal cortex and frontal regions to play a crucial role in memory (McKenna et al., 2017; Takehara-Nishiuchi, 2014). Notably, this association did not survive an age correction (i.e. associations were age-dependent). This suggests that age-related maturation of identified regions may explain improvements in memory abilities. Indeed, previous literature looking at similar developmental populations (i.e. aged 6-13) have found older children to have better memory abilities (Garon et al., 2014). Our study suggests that these gains may be explained by maturation of identified clusters as children get older (Buss & Spencer, 2018). However, we note that a longitudinal study is necessary to look precisely at how maturation of these regions mediate improvements in memory abilities.

Finally, shifting abilities were associated with cortical thickness of the bilateral frontal and occipital lobes and left medial and anterior temporal lobes. Strikingly, many of these associations were uncovered after age was controlled for. Shifting abilities have been argued to be more complex than other EFs. Arguably, shifting abilities involve more complex processes such as attentional flexibility and monitoring of different task demands (Dajani & Uddin, 2015). This may explain why individual differences in cortical thickness of these multiple regions may be crucial in supporting the different processes involved in shifting abilities. Additionally, our findings could partially be explained by the age range in our sample. Previous findings show the developmental progression for shifting to be longer than other EFs (Davidson et al., 2006). Shifting abilities have been found to develop extensively even in adolescence, with substantial differences in abilities observed between adolescents and adults (Davidson et al., 2006). In our younger population, therefore, individual differences in cortical thickness in these clusters were particularly important in predicting better abilities. In particular, given that age was associated with cortical thinness in an extensive number of regions (Supplementary Materials-2), controlling for age helped uncover true neural correlates (i.e. based on cortical thickness) of shifting abilities.

We note a couple of limitations. First, our findings are constrained to middle childhood, although executive functions do not have the same developmental trajectories and progressions. While inhibition abilities have been observed in children as young as four-years old, shifting abilities continue to develop in adolescence (Davidson et al., 2006). Therefore, in particular, age-controlled associations should be interpreted with this developmental population in mind. Further, we have used cross-sectional data to examine neural correlates. Therefore, we are only able to interpret our findings as brain-behaviour associations (i.e. looking at underpinnings of executive functions). A longitudinal design would have allowed us to use mediation models to examine how brain maturation could explain increases in abilities.

Our paper has important implications. Our research helps identify the true neural underpinnings of executive functions. Using our multi-measurement approach allows us to clarify and reconcile previous findings (McKenna et al., 2017; Tamnes et al., 2010). Understanding the neural underpinnings of executive functions could help us understand clinically relevant behaviours, characterised by executive function deficits (Mar et al., 2022; Wodka et al., 2007).

In sum, using a multi-measurement approach, we clarify the neural correlates of inhibition, memory and shifting abilities. While age-dependent neural correlates of memory were identified, age-independent neural correlates of shifting abilities were identified. Our findings demonstrate the importance of using a multi-measurement approach to measure executive functions to reduce measurement impurity issues that may prevent uncovering true neural correlates.

2.6. Supplemental Materials-2

2.6.1. Detailed Description on cortical thickness and age

Age was positively associated with one cluster in the right frontotemporal lobe consisting of the entorhinal cortex, fusiform gyrus, lateral orbitofrontal cortex, superior temporal gyrus and temporal pole. For the other nice clusters, age was negatively associated with cortical thickness. Five of these clusters were located on the left hemisphere. One cluster was observed in the left caudal anterior cingulate cortex, posterior cingulate cortex and corpus callosum. Two of these clusters were observed in the left frontotemporal lobe consisting of the lateral orbitofrontal cortex, pars triangularis, precentral gyrus, postcentral gyrus, insular cortex, superior temporal gyrus, and transverse temporal cortex. One cluster was observed in the left occipitotemporal lobe consisting of the lateral occipital cortex, fusiform gyrus, and inferior temporal gyrus, with another located in the left parieto-occipital lobe consisting of the superior parietal gyrus, precuneus, cuneus, lateral occipital gyrus, lingual gyrus, and pericalcarine. The other four clusters were located in the right hemisphere. Two clusters were observed in the right frontal lobe; the first consisting of the medial orbitofrontal cortex, rostral anterior cingulate, and superior frontal gyrus, and the second (i.e. frontoparietal lobe specifically) consisting of the precentral gyrus, postcentral gyrus, and supramarginal gyrus. One cluster was observed in the right parietotemporal lobe consisting of the supramarginal gyrus, insular cortex, superior temporal gyrus and transverse temporal cortex. Finally, the last cluster was observed in the right parieto-occipital and parietotemporal lobes consisting of the precuneus, cuneus, lateral occipital gyrus, lingual gyrus, pericalcarine, fusiform gyrus as well as the cingulate cortex (i.e. specifically isthmuscingulate).

Chapter 3. Comparing inhibition and context monitoring as a mechanism underlying cognitive control

Part of Chapter 3 has been written in preparation for publication and is available as a preprint. Ganesan, K., Smid, C., Cañigueral, R., Thompson, A., & Steinbeis, N. (preprint) Not context monitoring but inhibition plays a privileged role in childhood cognitive control. https://doi.org/10.31234/osf.io/kuebx

3.1. Abstract

Childhood cognitive control is an important predictor for positive development, yet interventions seeking to improve it have provided mixed results. This is partly due to lack of clarity surrounding mechanisms of cognitive control, notably the role of inhibition and context monitoring. Here we use a randomized controlled trial to causally test the contributions of inhibition and context monitoring to cognitive control in childhood. Sixty children aged 6 to 9-years were assigned to three groups training either inhibition, context monitoring or response speed using a gamified, highly variable and maximally adaptive training protocol. Whereas all children improved in the targeted cognitive functions over the course of training, pre-post data show that only the inhibition group improved on cognitive control. These data support a privileged role of inhibition in cognitive control during childhood. Further, gamified and maximally adaptive interventions hold promise for improving cognitive control at developmental periods of heightened plasticity.

3.2. Introduction

Imagine going out for a meal with colleagues, after a long day at the office, which has made you very hungry. Your food comes to your table before everyone else's and you are able stop yourself from taking a bite. How are you able to control your pre-potent response? On a daily basis, people need to control and direct their thoughts and actions. Also known as cognitive control, this term describes a set of processes that support flexible goal-directed behavior (Botvinick et al., 2001; Botvinick & Braver, 2015). Childhood cognitive control is predictive of later life success and well-being (Blair & Razza, 2007; Bull et al., 2011; Clark et al., 2010; Moffitt et al., 2011) and as such its study occupies a key position in child development research. The importance of cognitive control for positive development coupled with increased neural plasticity during childhood (Bunge & Zelazo, 2006; Kolb & Gibb, 2011; Wass et al., 2011) has made it a primary target for interventions, but the precise mechanistic targets are still debated. Inhibition has long occupied a prominent role in cognitive control (Aron, 2007). More recently however it has been suggested that this can instead be subsumed by other cognitive processes, notably context monitoring (Chatham et al., 2012; Hampshire et al., 2010; Sharp et al., 2010). Understanding the mechanisms constituent of cognitive control is key to optimizing interventions aimed at improving this critical life skill. To examine the causal role of inhibition and context monitoring in cognitive control during childhood we used a 6-week training protocol, testing for the effects of training on several indices of cognitive control. We show that both inhibition and context monitoring improved during the course of training, but that only inhibition led to changes in several indicators of cognitive control.

Inhibition has long been considered to be at the core of cognitive and behavioral control (Aron, 2007). Factor analyses of executive function in middle childhood have consistently yielded inhibition (Hartung et al., 2020; Messer et al., 2018; St Clair-Thompson & Gathercole, 2006) which in turn has been underpinned by a circumscribed neural network of brain regions including right inferior frontal gyrus (Aron et al., 2003). More recently it has been argued that the ability to inhibit unwanted thoughts or actions depends as much on monitoring the environment for contextual cues that indicate the need to change action (Chatham et al., 2012; Dodds et al., 2011; Hampshire et al., 2010). Evidence in support of this view comes from tasks matched on context monitoring but with different motoric demands (e.g., requiring a double key press instead of inhibition in response to signal). In adults, it was demonstrated that multiple neural and behavioural signatures of response inhibition tracked monitoring demands more closely than motoric-stopping demands, and behavioral measures of context monitoring efficacy, but not stopping efficacy, predicted both response inhibition performance and associated rIFG activation (Chatham et al., 2012). According to this account, inhibition can be subsumed by a more general process of action selection (i.e. selecting between initiation and inhibition of action).

This revised account has not remained unchallenged (Aron et al., 2014). It has been argued that any infrequent stimulus (as is the case in virtually all studies arguing for a context monitoring account) require some form of inhibition (Aron et al., 2014). Further, the literature on Pavlovian response biases, where appetitive cues are inherently associated with Go responses and aversive cues with No-Go or Stop responses (Guitart-Masip et al., 2011), suggests that approach and avoidance (i.e. inhibition) are underpinned by fundamentally different processes. In sum, there remains substantial controversy over core processes of cognitive control. This controversy finds itself also in the developmental literature, where standard views of the primacy of response inhibition in cognitive control (Diamond, 2009) contrast with more recent accounts advocating for a core role of context monitoring (Chevalier et al., 2014; Winter & Sheridan, 2014). Given the importance of understanding the core processes of cognitive control in order to tailor interventions to foster this crucial skill early in life, causal evidence is needed.

A recent study in 7- to 9-year old children practicing either stopping an ongoing action or monitoring for cues that signalled the need to ‘go-again’ showed that practicing either activity improved response inhibition scores, but that children who had practised monitoring outperformed the inhibition group (Chevalier et al., 2014). However, this study only looked at the effects of different instructions after practice, rather than behavioural change, and failing to investigate how this could transfer to independent pre-post measures. Group differences could therefore also be attributed to pre-existing individual and task-related differences. As such, causal evidence for a unique role of context monitoring in cognitive control is still lacking. To remedy this, we used a pre-post design looking at the effects of inhibition training and context monitoring training on several indicators of cognitive control. We further included a control group training in response speed.

Training studies offer considerable leverage for causal inference on the involvement of key mechanisms (Chatham et al., 2012; Chevalier et al., 2014; Knoll et al., 2016). While working memory and cognitive flexibility have received most empirical attention, there is less work on the effects of inhibition training on cognitive control. This is in large parts due to early attempts proving unsuccessful leading to the premature conclusion that inhibition is too automatic a process to be trained (J. R. Cohen & Poldrack, 2008). More success at demonstrating the plasticity of inhibition has been shown recently using more adaptive training regimes (Berkman et al., 2014; Biggs et al., 2015; Delalande et al., 2020; Verbruggen et al., 2013; Zhang et al., 2019). Moreover, a more fine-grained look at different types of cognitive control has been recommended (i.e. pro- and reactive control; Berkman et al., 2014). While proactive control can be viewed as “early selection” in which goal-relevant information is actively maintained in a sustained manner before the occurrence of a cognitively demanding event, reactive control is activated as required, such as after the detection of a cognitively demanding event (Braver, 2012; Braver et al., 2009). One recent study has shown that adults who had trained inhibition compared to a so-called sham training group exhibited neural activation patterns indicative of a shift from reactive to proactive cognitive control (Berkman et al., 2014).

Here we examine the role of inhibition and context monitoring respectively in cognitive control. 60 children underwent a 6-week training of either inhibition, context monitoring or response speed, the latter of which served as a control for any generic training effects of inhibition and context monitoring. We hypothesised that training should lead to improvements in the targeted cognitive skill during the training. Further, we hypothesised differences between the three training groups on pre-post measures of cognitive control. We used behavioural indices of proactive control to further characterise the role of inhibition and context monitoring in cognitive control. We included an active control group training in response speed for which we did not expect any transfer onto measures of cognitive control.

3.3. Materials and Methods

3.3.1. Participants

Participants were children aged between 6.17 – 10.83 years (*M* = 8.25 years, *SD* = 0.87) from three different London schools. A convenience sample of 60 typically developing children (27 males, 33 females) were tested. Parental consent was obtained beforehand and the study was approved by the University College London research ethics committee (Protocol number: 12271/001). Children were tested onsite in a classroom by different researchers. Data collection occurred before and after the training. Training was delivered over a six-week period. Full pre-post data for our dependent variables was available from 57 participants for the Stop Signal Reaction Task (SSRT) and from 56 participants for the AX-Continuous Performance Test (AX-CPT). Each child was assigned to one of three groups: response inhibition, context monitoring, and response speed (Table S1*).*

3.3.2. General Procedure

During pre- and post-training test sessions, all participants were tested for approximately one-hour at their school, where they completed the behavioural tasks on a laptop. In the following 6-weeks, they participated in one or two training sessions per week with an experimenter in their school and were encouraged to engage in three additional training sessions at home, where they could access the same training games online.

3.3.3. Training Games

For each group, the training games were presented in the same manner and with the same conceptual narrative (Figure 3-1), however the participant instructions varied according to the particular domains being trained. The overall narrative given to the participants was that they had crashed their plane in the desert. In order to return home, they will navigate through different four locations (i.e. forest, desert, snow, mountain), within which they must complete several of six individual games, enabling them to move to different locations on a map in order to meet a wise man who endows them with spare parts to fix their plane. After completing the first half of the games, they reach the wise man from whom they need to return to their plane.

Every session consisted of two of the games, and lasted for approximately 15 minutes. Number of trials and the number of required key presses differed per game, however the overall time spent playing within a session was equivalent across the different groups. The mechanistic aspect of the games differed across the different groups in the following ways: In the inhibition group, participants had to press the spacebar to respond to a go-signal, or refrain from pressing the spacebar when a stop signal appeared, essentially analogous to an SSRT. Games in this group used a staircase design that changed the Stop-Signal Delay (SSD) in steps of 50ms according to the one-up-one-down procedure to create an adaptive design (Logan, 1997; Verbruggen & Logan, 2009), and was set to be 200ms at the start. A successful stop trial would decrease the SSD by 50ms, while an unsuccessful stop-trial would increase it by 50ms. For the context monitoring group, participants had to press the spacebar in response to a go-signal and press the spacebar twice when presented with a ‘Double-go’ signal (Chatham et al., 2012). The same staircasing procedure was used as in the inhibition group. For the response speed group, participants were simply instructed to press the spacebar as fast as possible. To make training adaptive for this group, a threshold was introduced that consisted of a rolling average of the response time of the previous ten trials plus two standard deviations. This ensured adaptive training mechanisms for all three training groups (for more details on the training, see *Supplementary Materials-3*).

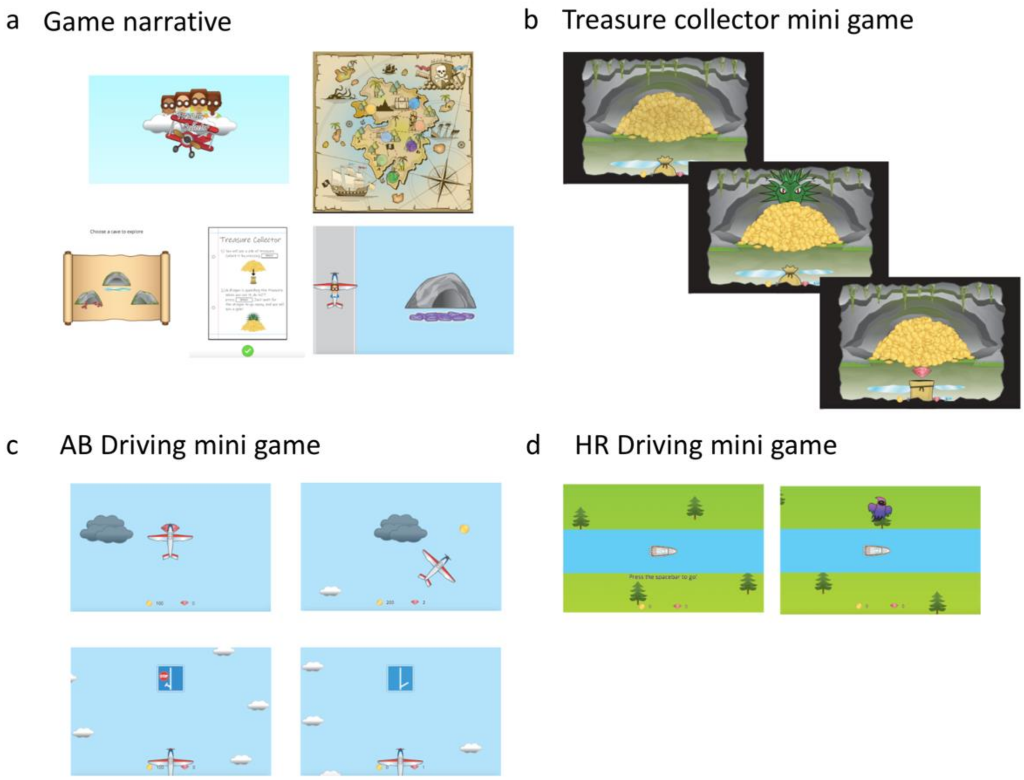


Figure 3-1. (a) An illustration of the overall narrative of the games, (b) Example images of the Treasure Collector game, (c) Example images of the AB Driving game, (d) Example images of the HR Driving game.

3.3.4. Motivation

At the end of each training session, participant could choose to complete a bonus game which was a shortened version of one of the six games, to get additional points. The choice to participate in bonus games was logged as a motivational measure. In addition, participants filled in a questionnaire regarding their motivation to participate in the training every week at school (available in *Supplementary Materials-3*). There was a total of 6 items on a 6-point scale (i.e. ‘Completely Agree’ to ‘Completely Disagree’). Negative items were reverse coded and a motivational score for each week was calculated by combining scores for the 6 items.

3.3.5. Pre-Post Tasks

3.3.5.1. Stop-Signal Response Task.

As a measure of response inhibition, we used a modified and child-friendly version of the SSRT (Logan & Cowan, 1984; Matzke et al., 2018). Participants were instructed to press the spacebar as fast as possible when seeing a honey pot centrally located on the screen (i.e. go-trials). On 25% of the trials, a stop-signal (picture of bees) was presented with a variable delay (SSD) after the stop-signal. Participants were instructed to not press the spacebar if bees appeared after a honey pot (i.e. stop-trials). If participants did not respond after 600ms, the honeypot disappeared. An intertrial-interval (i.e. fixation cross) was presented for 1250ms before the presentation of the next trial. The task had a staircase design with changes in steps of 50ms in the Stop-Signal Delay (200ms) with a starting SSD of 200ms. The SSD was then adjusted according to a tracking-procedure to achieve a 50% inhibition rate (Verbruggen & Logan, 2009), increasing the SSD by 50ms after a successful stop trial and decreasing it by 50ms after an unsuccessful stop-trial (one-up-one-down procedure, Logan, 1997). 10 practice trials were administered where feedback was provided, followed by the main task consisting of 60 go-trials and 20 stop-trials. No exclusion criteria was applied.

3.3.5.1. AX-CPT

Reactive and proactive control were measured using a child-friendly version of the AX-CPT paradigm (Chatham et al., 2009). The task was introduced as the Fruit Island game. An A or B cue (i.e. dog or cat) were presented in the middle of the screen for 500ms followed by an inter-stimulus interval of 750ms and then a probe X or Y (orange or apple) during which participants had to make their response. Participants had a maximum of 6000ms to make a response. Participants were instructed to press the left key whenever an X followed an A (i.e. AX trials) and to press the down arrow key for the presentation of all other cue-probe combinations. Importantly, they were instructed to only respond once the probe had been presented and were alerted of this if they made a response before the probe was presented. Responses were followed by an inter-trial interval of 1500ms. The proportions of the trial types were based on previous literature where 40% of trials were AX trials. All other trials (i.e. AY, BX, BY trials) were presented 20% each (Richmond et al., 2015). Trials were presented randomly. 10 practice trials were administered where feedback was provided followed by 60 main trials. No exclusion criteria was applied.

3.3.6. Statistical Analysis

3.3.6.1. Training Data

For the response inhibition, measures of mean SSRT, SSD and reaction times were calculated using the integration method (Verbruggen et al., 2013, 2019). According to previous recommendations, rules were implemented in the calculation of the indices (Verbruggen et al., 2019; *Supplementary Materials-3*). For the context monitoring group, reaction times on correct context monitoring trials (corrRTCM) and Context Monitoring Signal delay (CMSD) were calculated. Training success was measured based on the slope of mean SSRT and corrRTCM for response inhibition and context monitoring groups respectively. For the response speed group main outcome measures were CorrGoRT and the duration of stimulus presentation

(StimDur) as a measure of adaptive difficulty in the task similar to the signal delay. Reaction times were included that were within 2 standard deviations of the mean reaction time per participant. Stimulus presentation durations of more than 10 seconds in length were excluded as these indicate performance on the games was not normal. Full information on sessions and data cleaning can be found in the *Supplementary Materials-3*.

We used multilevel modelling with sessions at the first level and participants at the second level, and our outcome measures (i.e. mean SSRT, SSD, reaction time) as the dependent measure using the lme4 package in R (Berkman et al., 2014). We investigated whether changes in the dependent measures over sessions for participant were better explained by a null model (model0 = Dependent Measure (DM) ~ 1 + (1 | Participant)), a model with random intercept and fixed slope (model1 = DM ~ Session + (1 | Participant)), or a model with a random intercept and slope per participant (model2 = DM ~ Session + (1 + Session | Participant)). Model fits were compared with a chi square test, and results from the best fitting model are reported in the results (for further information on the multilevel modelling see *Supplementary Materials-3*). Package lmerTest in R was used to acquire p-values (Kuznetsova, Brockhoff & Christensen, 2017) and confidence intervals were computed using bootstrapping, via the package boot in R.

3.3.6.2. Training related changes

Based on previous guidelines, for the SSRT, reaction times below 100ms and above 5000ms were excluded (Luce, 1986). To analyse response inhibition derived from the SSRT, we calculated a *mean SSRT* estimate using the integration method (Verbruggen et al., 2013, 2019). Along with this, we used measures of mean SSD and correct inhibition (%) to measure response inhibition. To obtain a measure of proactive control, we examined the difference between AY and BX trials for both reaction times and error rates. Using this method, a larger value indicates tendency to employ proactive rather than reactive control while a smaller value indicates tendency to employ reactive rather than proactive control. To examine any changes in our measures pre- and post-training, repeated measures analyses were performed using mixed model ANOVAs with time point as a within-subject-factor and training group as a between-subject factor. Any significant interactions were further explored using paired sample t-tests.

3.4. Results

3.4.1. Training motivation and adherence

There was no significant difference in the total number of sessions attempted between the groups, (response inhibition group: *M* = 7.84, *SD* = 3.45; context monitoring group: *M* = 9.81, *SD* = 5.92; response speed group: *M* = 9.50, *SD* = 5.31, *F* (2,57) = .86, *p* = .428, *95% CI* [-1.58, 4.89]). After applying the exclusion criteria for sessions (see *Supplementary Materials-3*), there was still no significant difference between the groups for sessions included for analysis, (response inhibition group: *M* = 5.74, *SD* = 2.18; context monitoring group: *M* = 7.00, *SD* = 3.55; response speed group: *M* = 7.74, *SD* = 4.82, *F* (2,55) = 1.44, *p* = .246, *95% CI* [-.39, 4.39]).

There was no significant difference between the groups in the percentage of bonus games completed for the total number of sessions, (response inhibition group: *M* = 33.03, *SD* = 19.81; context monitoring group: *M* = 42.45, *SD* = 23.37; response speed group: *M* = 44.39, *SD* = 23.79; *F* (2,57) = 1.42, *p* = .250, *95% CI* [-3.05, 25.76]). There was also no difference in motivation scores over time between the groups (response inhibition: *M* = 62.98, *SD* = 30.90; context monitoring: *M* = 72.19, *SD* = 32.68; response speed: *M* = 71.09, *SD* = 36.44; *F* (2,212) = 1.63, *p* = .199, *95% CI* [-2.94, 19.28]).

3.4.2. Response inhibition group

There was a significant negative main effect of session on SSRT, showing that the response inhibition group became significantly better at inhibiting over sessions, (*F* (1,254.4) = 5.97, *p* = .015, *95% CI* [-32.43, -3.16]; slope for session: *beta* = -18.30, *t* = -2.44, *se* = 7.49; Figure 3-2). There was a significant increase in the mean SSD values over sessions, (*F* (1,257) = 16.45, *p* <.001, *95% CI* [14.20, 40.18]; individual slope for session: *beta* = 27.68, *t* = 4.01, *se* = 6.83). There was a significant change in reaction time over sessions (*F* (1,256.41) = 4.88, *p* = .028, *95% CI* [2.00, 20.60]; slope for session: *beta* = 11.21, *t* = 2.21, *se* = 5.07).

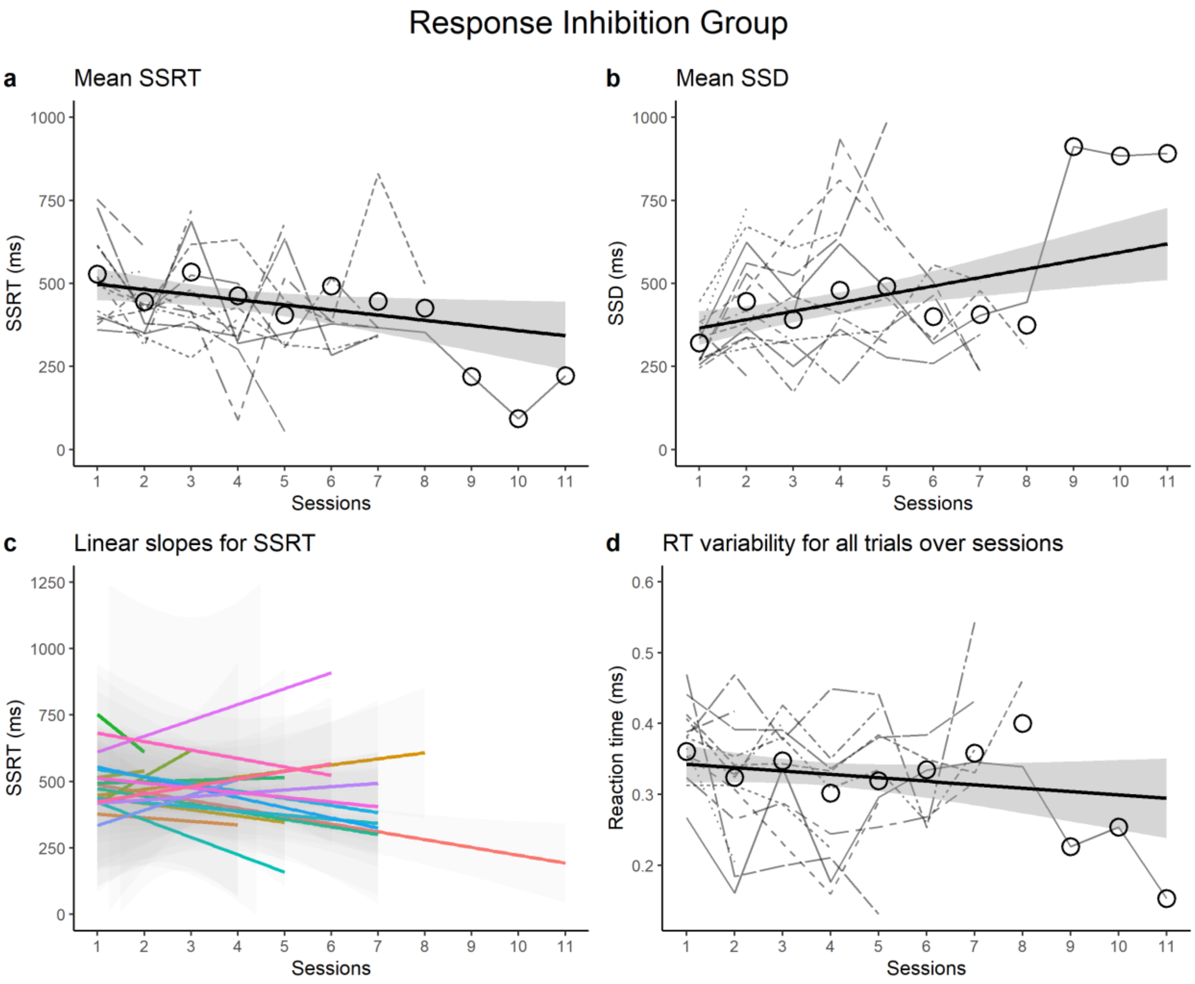


Figure 3-2. Changes in measures as a function of training in the response inhibition group.

3.4.3. Context monitoring group

There was a significant main effect of session on corrRTCM, showing that the context monitoring group became significantly faster at correctly answering context monitoring trials over sessions, (*F* (1,220.71) = 8.46, *p* = .004, *95% CI* [-21.32, -4.06]; slope for session: *beta* = -12.44, *t* = -2.91, *se* = 4.28; Figure 3-3). There was a significant increase in the mean CMSD values over sessions, (*F* (1,250.98) = 15.24, *p* <.001, *95% CI* [7.29, 22.71]; individual slope for session: *beta* = 14.76, *t* = 3.90, *se* = 3.78; Figure 3), showing that the participants became better at the task. There was no significant change in CorrGoRT over sessions (*F* (1,234.24) = 0.69, *p* = .408, *95% CI* [-10.72, 5.12]; slope for session: *beta* = -3.31, *t* = -0.83, *se* = 4.00; Figure 3-3).

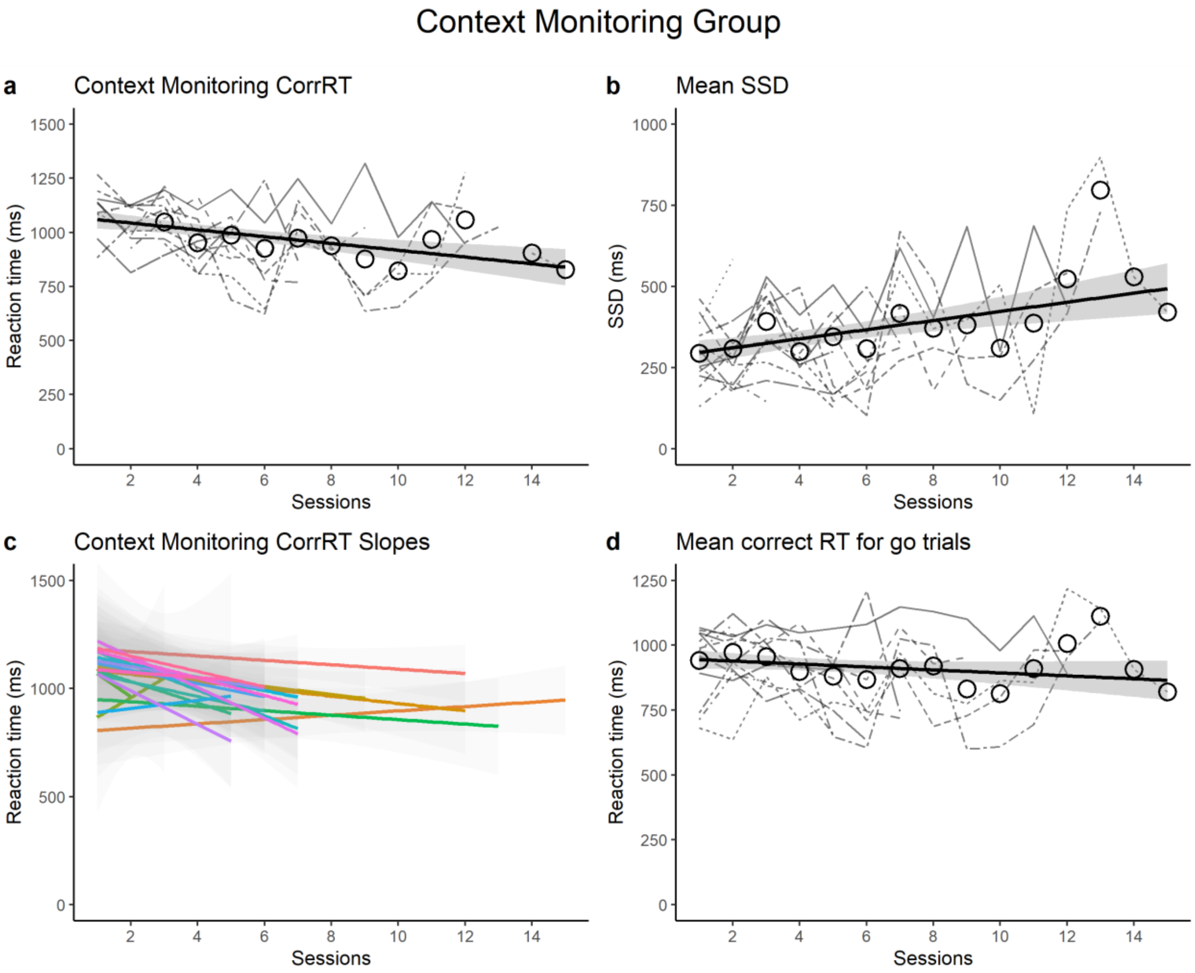


Figure 3-3. Changes in measures as a function of training in the context monitoring group.

3.4.4. Response speed group

There was a significant main negative effect of session on CorrGoRT, showing that the response speed group became significantly faster over sessions, (*F* (1,306.33) = 49.76, *p* <.001, *95% CI* [-21.19, -12.23]; slope for session: *beta* = -16.61, *t* = -7.05, *se* = 2.35; Figure 3-4). StimDur significantly decreased over sessions, (*F* (1,303.1) = 4.62, *p* = .032, *95% CI* [-37.92, -1.48]; slope for session:

beta = 19.62, *t* = -2.15, *se* = 9.13; Figure 3-4), showing that the participants improved at the tasks over sessions.

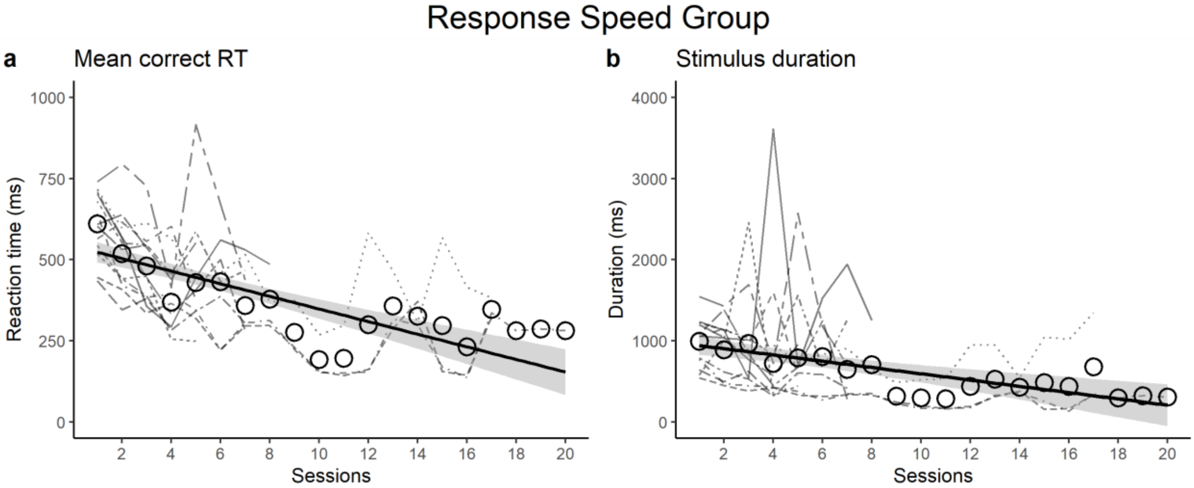


Figure 3-4. Changes in measures as a function of training in the context monitoring group.

3.4.5. Training-related changes in response inhibition

Using all three measures of response inhibition (i.e. mean SSRT, mean SSD, correct inhibitions) as a criterion showed significant interactions between group and timepoint (Table 3-1, Table 3-2, Table 3-3). To further examine these interactions, paired t-tests were used to investigate the effect of training in the different groups.

For the response inhibition group there was a significant reduction in mean SSRT (*t* (17) = 2.10, *p* = .05), a significant increase in mean SSD (*t* (17) = -3.62, *p* = .02) and a significant increase in correct inhibitions (%) (*t* (17) = -3.01, *p* = .01) between pre- and post-training (Figure 5a-c). For the context monitoring group, there was a significant increase in mean SSRT (*t* (19) = 2.24, *p* = .04), but no significant change for mean SSD (*t* (19) = -0.47, *p* = .65) and correct inhibitions (%) (*t* (19) =

0.17, *p* = .87) between pre- and post-training (Figure 5a-c). For the response speed group, there were no significant differences in mean SSRT (*t* (17) = 1.06, *p* = .30), mean SSD (*t* (17) = 0.79, *p* = .44) or correct inhibitions (%) (*t* (17) = 0.30, *p* = .77) between pre- and post-training (Figure 3-5a-c). There was a significant change in reaction time on go trials in the response inhibition group (*t* (17) = -2.88, *p* = .010) but not in the context monitoring or response speed group (*p* > .068; Figure 3-5d). Because we were specifically interested in the effects of the different types of cognitive control training on outcome measures, we also compared these two groups directly. There were significant pre-post differences in all three measures between response inhibition and context monitoring groups (Table 3-6), where the response inhibition group benefited significantly more from the training than the context monitoring group.

None of our cognitive control measures at pre-test predicted training success in either response inhibition or context monitoring groups (p > .114). Training success did not predict changes in mean SSRT in either group (*p* > .153).

3.3.6. Training-related changes in proactive control

We examined how proactive control changes with training. Analysis revealed a non-significant interaction between group and timepoint for proactive control based on reaction time (Table 3-4). There was a marginally significant interaction between group and timepoint for proactive control based on error rates (Table 3-5). To further examine this trend, paired t-tests were used to investigate the effect of training in the different groups. As predicted, in the response inhibition group, proactive score (%) significantly increased between pre- and post-training (*t* (16) = -2.60, *p* = .019). There were no significant differences in proactive score (%) in both the context monitoring (*t* (15) = 0.96, *p* = .35) and response speed groups (*t* (16) = -1.29, *p* = .21) between pre- and post-training (Figure 3-5e). We also compared the two cognitive control training groups on this outcome measure and found a significant difference between pre-post changes in proactive score (%) between the response inhibition and context monitoring group (Table 3-6). Proactive control measures at pre-test were not associated with training success (*p* > .587) in either response inhibition or context monitoring group. In neither training group, did training success predict changes in proactive control score (*p* > .332).

Table 3-1. Results from Mixed ANOVA examining mean SSRT.

Predictor	df_{Num}	df_{Den}	*F*	*p*
(Intercept)	1	54	609.34	.000
Group	2	54	0.34	.713
Timepoint	1	54	0.11	.742
GroupxTimepoint	2	54	5.18	.009

Table 3-2. Results from Mixed ANOVA examining mean SSD.

Predictor	df_{Num}	df_{Den}	*F*	*p*
(Intercept)	1	54	399.31	.000
Group	2	54	3.52	.037
Timepoint	1	54	3.97	.051
GroupxTimepoint	2	54	5.68	.006

Table 3-3. Results from Mixed ANOVA examining correct inhibitions (%).

Predictor	df_{Num}	df_{Den}	*F*	*p*
(Intercept)	1	54	1643.12	.000
Group	2	54	1.11	.336
Timepoint	1	54	2.49	.121
GroupxTimepoint	2	54	3.83	.028

Table 3-4. Results from Mixed ANOVA examining proactive control score (s) based on reaction times.

Predictor	df_{Num}	df_{Den}	*F*	*p*
(Intercept)	1	53	17.37	.586
Group	2	53	1.75	.407
Timepoint	1	53	0.58	.647
GroupxTimepoint	2	53	0.75	.241

Table 3-5. Results from Mixed ANOVA examining proactive control score (%) based on error rates.

Predictor	df_{Num}	df_{Den}	*F*	*p*
(Intercept)	1	53	4.37	.887
Group	2	53	2.31	.188
Timepoint	1	53	2.49	.211
GroupxTimepoint	2	53	2.93	.064

Table 3-6. Comparisons from independent t-tests of response inhibition and context monitoring groups based on pre-post changes in cognitive control indices.

	Response Inhibition Group	*Context Monitoring Group*		
	M (SD)	M (SD)	t-statistic	p-value
mean SSRT (s)	-0.05 (0.09)	0.06 (0.12)	-3.03	.004
mean SSD (s)	0.11 (0.03)	0.01 (0.11)	2.48	.018
Correct inhibitions (%)	0.09 (0.13)	-.00 (0.12)	2.43	.020
Proactive control (%)	0.12 (0.19)	-0.06 (0.26)	2.31	.027

Note: Decrease in mean SSRT indicated increase in cognitive control. Increases in mean SSD, correct inhibitions and proactive control scores indicated increase in cognitive control.

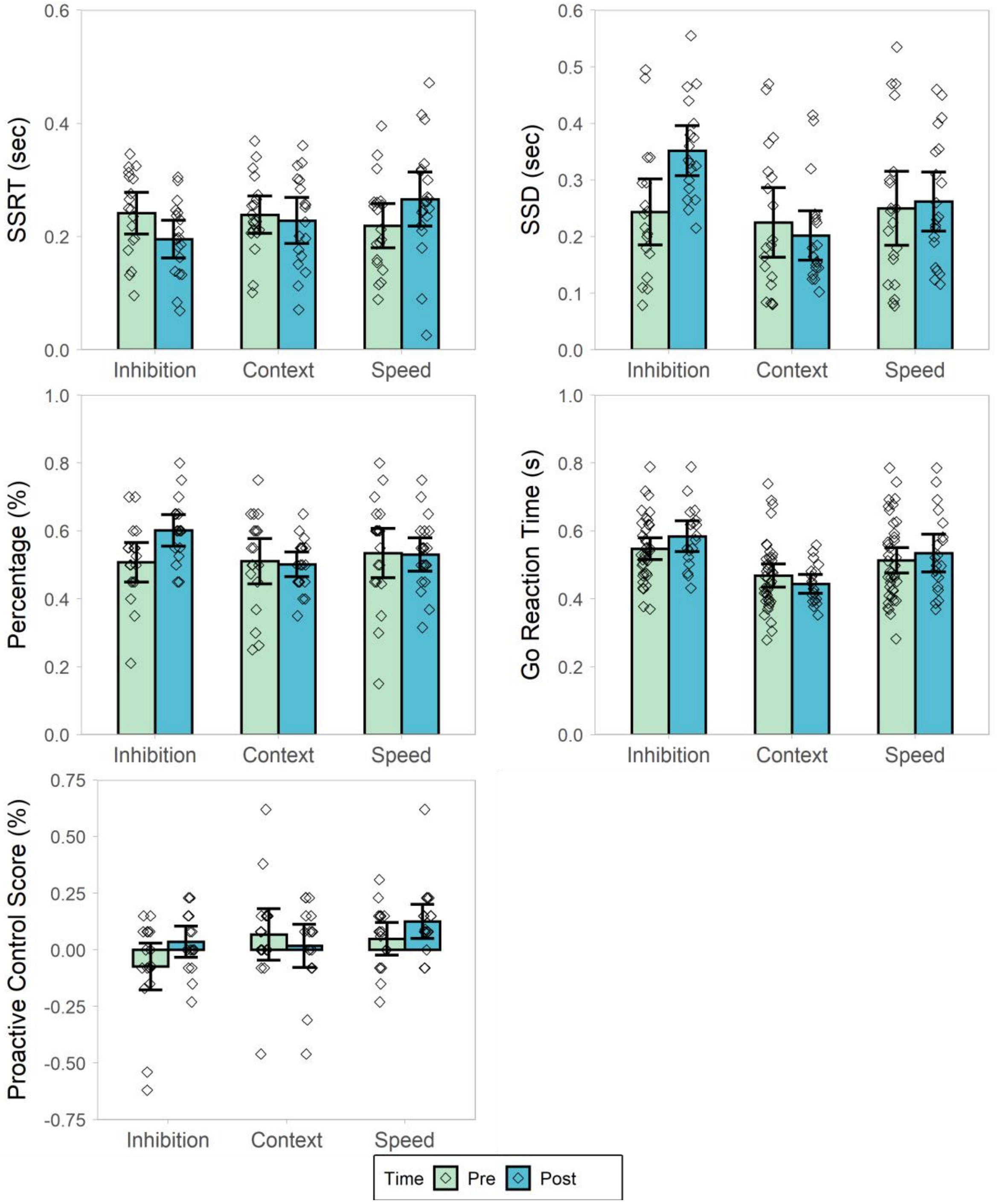


Figure 5. Pre-post test changes of mean SSRT, SSD, correct percentage inhibitions and proactive control (%) in all three groups.

3.4. Discussion

This study addressed the nature of processes underlying cognitive control during childhood, namely response inhibition and context monitoring. To provide causal evidence we leveraged a randomized control trial design and compared how training different cognitive processes impact cognitive control. Training involved 6 weeks of practicing either response inhibition, context monitoring or response speed. All groups improved on the cognitive domains that were trained, demonstrating that the adaptive training was successful. Crucially, pre-post-test comparisons on several measures of cognitive control revealed that only inhibition training successfully improved cognitive control. These findings demonstrate that response inhibition (and not context monitoring) plays a privileged role in cognitive control during childhood. This helps to resolve a long-standing debate in the field and points towards fruitful directions in terms of interventions aiming to improve this crucial skill.

We employed an adaptive intervention to improve effectiveness of training (Cuenen et al., 2016), in a gamified format suitable for children. This ensured that training was adjusted to each individuals' ability and that training success was therefore maximised in all training groups. This also suggests that all training groups are likely to equally benefit from training and any differences in training effects are unlikely to be pre-existing explained by individual differences. Finally, training was equally engaging for all groups with no reported differences in motivation. This helps to rule out any potential confounders of group differences (in terms of either training effectiveness or motivation) accounting for our observations.

We used this gold standard training design to investigate how specific training regimes lead to improvements in cognitive control, by measuring transfer to novel tasks. We showed that post-training improvements in cognitive control are only observed in the group training response inhibition. Our findings are buttressed by evidence of a shift from reactive to proactive control observed in the response inhibition group only. This finding is in line with a previous study in adults, which found that response inhibition training led to changes in brain activity indicative of greater proactive control following training (Berkman et al., 2014). Training response inhibition thus not only induces improvements during training but also transfers to other contexts. This reinforces the privileged role response inhibition may hold as compared to context monitoring.

Despite improvements of context monitoring abilities during training, this did not transfer to pre-post measures of cognitive control. In fact, we report a surprising decline on a pre-post measure of cognitive control after training in the context monitoring group. This contrasts with previous findings showing positive effects of context monitoring practice on cognitive control (Chevalier et al., 2014). Several reasons might account for these discrepant findings. First, previously used pre-post test stimuli were similar to those used for practice (Chevalier et al., 2014). Thus, context monitoring may only improve cognitive control measures when both practice and outcome measures are based on similar stimuli, suggesting that practice of context monitoring may improve processing of cues specific to monitoring but not an underlying cognitive skill. Second, there might be a critical difference in the extent of time dedicated to improving the skill in question. While practicing both inhibition and context monitoring in the short term can enhance cognitive control (Chevalier et al., 2014) our study suggests that, training more extensively and over longer periods the effects of these training paradigms differentiate. Thus, over short periods of time, both response inhibition and context monitoring practise improve monitoring capacities, but over longer periods, the action (going vs stopping) becomes more impactful. This may have led to more inconsistent inhibitions when the stop signal is presented in the context monitoring group, leading to a decline in cognitive control post-test. This points towards key differences in the underlying mechanisms involved – where for example, in the short term, heightened responsiveness to cues may lead to an overall increased ability to respond to stimuli (leading to generally improved performance, including in a response inhibition task), which over the longer term, if this is not paired with motoric response inhibition, is not sufficient. Despite finding similar engagement in both inhibitory and context monitoring group, it may be possible that the cognitive load associated with monitoring was too high that caused children not to learn and benefit from it. However, as we do not have a measure of cognitive load or mental demand, we are unable to test this. Future research may benefit from examining the cognitive load associated with different training regimes and how this may affect training gains.

One potential issue that may warrant consideration is how generalisable our findings may be. We recruited and tested participants from three schools that were willing to be part of our study which may have potentially biased our results. Future findings should recruit from a range of different schools with more diverse demographics. Despite this, our study contributes to the cognitive control field significantly. Training can be costly and therefore, it is important to establish the mechanism underlying cognitive control. Our findings suggest that the type of mechanism targeted by interventions is not a trivial matter and may produce different changes in cognitive control. This is important as recommendations for training based on mechanism will differ as well – where inhibition may target improving ability to stop actions, context monitoring focuses on broadening attentional focus (Chatham et al., 2012; Messer et al., 2018). Importantly, it is crucial for researchers to adopt a clear framework when considering training cognitive control as this may help boost the effectiveness of training (Smid et al., 2020). In particular, after establishing the mechanism underlying training, it may be important to examine individual differences that may predict training and timepoints at which training may be most effective. Perhaps, some of these correlates as well as other pre-existing individual characteristics could even give us insight into variability observed in training success (Könen & Karbach, 2015).

Another key issue is the conceptualisation of our mechanisms. We set out to test inhibition vs context monitoring as mechanisms in our study. Based on the double-tap response the context monitoring group were required to give, a big assumption was made that context monitoring demands were higher in this group as compared to the response inhibition group. However, arguably context monitoring demands were similar with both training groups (i.e. saliency of cues were equal). For instance, in the inhibition training condition where participants were required to execute a different response on the basis of a 'go' vs 'stop' signal, it could be argued that monitoring of the different cues (i.e. signal) placed similar context monitoring demands. Therefore, our study shows that pairing context monitoring with motoric stopping is crucial for effective training. Instead, to have truly examined differences between inhibition and context monitoring, it would have been better to have reduced or eliminated the need for context monitoring in our inhibition training. We note this as a crucial limitation in the way this study was conceptualised, with future research necessary in solving this.

The present study is the first to use a gold-standard training intervention in a randomized control trial to causally test the contributions of response inhibition and context monitoring to cognitive control in childhood. Only the inhibition group improved on post-training measures of cognitive control. These findings help to resolve the debate around the key mechanisms facilitating cognitive control, suggesting that inhibition may have a privileged role in cognitive control during childhood. Inhibition training interventions such as the one used in the current study hold promise. However, we note some methodological constraints that future research should build upon.

3.5. Supplementary Materials-3

3.5.1. Information on training games.

Six training games were available for each group. These were Treasure collect, Mining, Chest picking, Conveyor belt, AB driving and Hold-and-Release (HR) driving. Each of these had 4 different settings (forest, desert, snow, mountain) which was randomly assigned based on an assignment table. The games playable varied per session. Participants were initially presented with a selection of caves that they could choose from before starting their game to encourage engagement (Johann & Karbach, 2020). For each game, the participant was presented with a narrative in which they were required to accrue points by collecting treasure, gems, or coins, whilst avoiding a perpetrator (dragon, monster, ghost). For all the games, participants were instructed to respond in a particular way to a certain stimulus, and respond in a different way to a different stimulus in order to collect points. These instructions varied in different ways across the three training groups, in order to train the targeted abilities (Table S3-1). For example, the three groups were given the following instructions for the Treasure Collector game:

- Response inhibition training group: “You will see a pile of treasure. Collect it by pressing ‘space’. A dragon is guarding the treasure. When you see it, do

NOT press ‘space’. Just wait for the dragon to go away, and you will win a gem!”.

- Context monitoring training group: “You will see a pile of treasure. Collect it by pressing ‘space’. A dragon is guarding the treasure. When you see it press ‘space, space’ to make the dragon to go away and you will win a gem!”
- Response Speed training: “You will see a pile of treasure. Collect it by pressing ‘space’. A dragon is guarding the treasure. When you see it, that means there is a precious gem in the treasure. Press ‘space’ as fast as you can to collect the gem!”

Table S3-1. Training assignment of participants.

Training group	N	Ages (in years)	Gender male (%)
Inhibition	19	8.84	42.11
Context Monitoring	21	8.37	55.00
Response speed	20	8.71	47.62

3.5.2. Training data cleaning process

As these games were being piloted and development of the games was still not entirely completed, there was a small percentage of errors in the raw data in the form of invalid key presses (<5%), incorrect coding of separate sessions by date, or session durations that went on too long (<5%). In order to accurately analyse the training data, invalid presses for the games were removed and sessions were trimmed if they continued on too long (15-minute duration per session). If more than 50% of trials were removed, the game was excluded from analysis. For SSRT calculation (where applicable), it was ensured that stop RT was larger than go RT and any negative SSRT values were removed (Verbruggen, 2019).

3.5.3. Responses for each group

Here, we outline the game mechanisms per the response inhibition group. For the Treasure collect, Mining, Chest picking and Conveyor belt game, valid responses were either spacebar presses or no responses. Any different key presses that were logged in the raw data (e.g. arrow key or enter presses) were excluded from the data (<5%). For the AB driving game, valid responses were the left and right arrow key, or no response. Any spacebar presses or other keys were excluded from the data (<5%). For the HR driving game, valid responses were spacebar release and no responses. Any other responses were excluded from the data.

Next, we will outline the game mechanisms per the response inhibition group. For the treasure collect, mining, chest picking and conveyor belt game and HR driving, valid responses were a single spacebar press, spacebar release, a double spacebar press or a no response. All arrow key responses (<5%) were excluded from the data. For the AB driving game, left, right and up arrow key responses and a 'none' response were valid responses. All others were excluded from the data (<5%).

Finally, we outline the mechanism for the response speed group. For the treasure collect, mining, chest picking and conveyor belt game and HR driving, valid responses were a spacebar press or a no response. All arrow key responses were excluded from the data (<5%). For the AB driving game, valid responses were left and right arrow keys or no responses. All other keys were excluded from the data (<5%). Appropriate response that needs to be given has also been summarised in Table S3-2.

Table S3-2. Table of stimulus-response instructions for each game, across the different training groups.

Game	**Stimulus**	**Response inhibition**	**Context Monitoring**	**Response Speed**
Treasure Collector	Treasure	Press space (go)	Press space	Press space
	Dragon	Do not press space (stop)	Double press space	Press space
Mining	Rock	Press space (go)	Press space	Press space
	Gem	Do not press space (stop)	Double press space	Press space
Chest picking	Wobbling treasure chest on the other side to your bag	Press space to move to other side (go)	Press space to move to other side	Press space to move to other side
	Wobbling treasure chest on the same side as your bag	Do not press space (stop)	Double press space	Do not press space
	Dragon	Press space to move away from the dragon (go). Do not press space if the dragon is on the other side (stop).	Double press space to avoid moving towards the dragon	Press space to move underneath the dragon
Conveyor belt	Wobbling treasure chest	Press space to change direction of the belt so that the treasure chest moves towards the bag (go).	Press space to change direction of the belt. Double press space to keep the same direction.	Press space to change direction of the belt so that the treasure chest moves towards the bag.
	Dragon	Avoid the chest with the dragon behind it by pressing space to change the direction (stop).	Avoid the chest with the dragon behind it by pressing space to change the direction. Double press	Move the chest with dragon behind it by pressing space to change the direction.

			space to keep same direction.	
AB Driving	Sign pointing left or right	‘Left’ or ‘Right’ arrow key (go)	‘Left’ or ‘Right’ arrow key	‘Left’ or ‘Right’ arrow key
	Stop sign	Do not press ‘left’ or ‘right’ arrow key (stop)	Press ‘upwards’ arrow key	Press ‘left’ or ‘right’ arrow key
HR Driving	*	Continuously hold space (go)	Continuously hold space	Continuously hold space
	Ghost looking at the front of your car	Stop holding space (stop)	Stop holding space	Stop holding space
	Ghost looking at back of your car	Keep holding space (go)	Keep holding space and press enter	Stop holding space

*In this game, the instructions are the opposite in that the participants are required to continuously hold space and *stop* holding space in response to certain stimuli.

3.5.4. Session recoding and inclusion

For all groups, sessions were recoded based on date, meaning any data logged on the same date would be grouped in the same session. Since the mechanisms of the games differed in terms of key presses and mechanisms tested (see training game tasks), we only included sessions for a participant that a) had a minimum of 2 games (e.g. if the session only consisted of one game it was not included in the mixed model analysis), and for the response inhibition group only, sessions that b) that had at least two games which both had valid (e.g. not negative or an SSRT value that could not be calculated) SSRT measures. For the response speed group, reaction times were included that were within 2 standard deviations of the mean reaction time per participant. Stimulus duration was adaptive on participant performance, and a stimulus duration of over 10 seconds meant that the participant reacted extremely slow. All further analysis for the training data for all three groups only included sessions that were not excluded based on these terms (e.g. also for the behavioural data analysis regarding accuracy).

3.5.5. Motivation Questionnaire.

The questionnaire consisted of 6 items (1*. I like the training*; 2. *I like to do the training*; 3*. I do not always feel like training*; 4. *I think I can become better through the training*; 5. *I find the training boring*; 6. *I am getting better at the training tasks)*. Items 3 and 5 were reverse coded.

3.5.6. Modelling for training measures

3.5.6.1. Response Inhibition group

First, we investigated whether change in SSRT over sessions for the participants was better explained by a null model (model0 = SSRT ~ 1 + (1 | Participant)), a linear model with random intercept and fixed slope (model1 = SSRT ~ Session + (1 | Participant)), or a linear model with a random intercept and slope per participant (model2 = SSRT ~ Session + (1 + Session | Participant)). A chi square test showed that model1, (-2LL = 3578.3, where −2LL is −2 * log-likelihood fit significantly better than model2, (2LL = 3576.9, AIC = 3588.9, BIC = 3610.2 ; X^2 = 5.873, *p* = .015) and the null model. We therefore used model1 for SSRT and sessions to report the following results for the response inhibition group. A chi square test showed that model1, (-2LL = 3529.5, AIC = 3537.5, BIC = 3551.7), also fit significantly better for SSD than model2, (-2LL = 3556.4, AIC = 3535.1, BIC = 3556.4; X^2 = 15.93, *p* = < .001) and the null model, so we used model1 to investigate changes in SSD over sessions. For reaction time on correct go trials (CorrGoRT), a chi-square test showed that model2, (-2LL = 3368.0, AIC = 3380.0, BIC = 3401.3), fit significantly better than model1 (-2LL = 3377.5, AIC = 3385.5, BIC = 3399.6; X^2 = 9.41, *p* = .009). However, fitting model2 led to a singular fit, probably due to the random effects structure leading to overfitting of the data, so we used model1 instead to report the following results.

3.5.6.1. Context monitoring group

First, we investigated whether change in correct RT for context monitoring trials (corrRTCM) over sessions for the participants was better explained by a null model (model0 = corrRTCM~ 1 + (1 | Participant)), a linear model with random intercept and fixed slope (model1 = corrRTCM~ Session + (1 | Participant)), or a linear model with a random intercept and slope per participant (model2 = corrRTCM~ Session + (1 + Session | Participant)). A chi square test showed that model1, (-2LL = 4434.2, AIC = 4442.2, BIC = 4457.3) fit significantly better than model2, (2LL = 4433.6, AIC = 4445.6, BIC = 4468.2 ; X^2 = 8.21, p = .004) and the null model. We therefore used model1 for corrRTCM and sessions to report the following results for the context monitoring group. For SSD, a chi square test showed that model1, (-2LL = 4450.2, AIC = 4458.2, BIC = 4473.4), also fit significantly better for SSD than model2, (-2LL = 4449.9, AIC = 4461.9, BIC = 4484.7; X^2 = 14.53, p <.001) and the null model, so we used model1 to investigate changes in SSD over sessions. For CorrGoRT, none of the models fit the data significantly better than the null model, and we therefore assume there was no change in CorrGoRT over sessions. We still reported these non-significant effects with the next best fitting model. The chi-square test showed that model2 was the better fit, (-2LL = 4492.4, AIC = 4504.4, BIC = 4527.2), but not significantly more than model1 (-2LL = 4496.5, AIC = 4504.5, BIC = 4519.6; X^2 = 4.03, p = .134). We used model2 to report the results.

3.5.6.2. Response speed group

We tested whether CorrGoRT over sessions for the participants was better explained by a null model (model0 = CorrGoRT ~ 1 + (1 | Participant)), a linear model with random intercept and fixed slope (model1 = CorrGoRT ~ Session + (1 | Participant)), or a linear model with a random intercept and slope per participant (model2 = CorrGoRT ~ Session + (1 + Session | Participant)). A chi square test showed that model1, (-2LL = 3983.9, AIC = 3991.9, BIC = 4006.8) fit significantly better than model2, (2LL = 3982.3, AIC = 3994.3, BIC = 4016.6 ; $X^2 = 45.76$, $p < .001$) and the null model. For StimDur, model1 was the best fit for the data, (-2LL = 4819.9, AIC = 4827.9, BIC = 4842.8) when compared to model2, (-2LL = 4819.7, AIC = 4831.7, BIC = 4854.1; $X^2 = 4.46$, $p = .035$) and the null model.

Chapter 4. Transfer to factors of executive functions through inhibition training.

Part of Chapter 4 has been written in preparation for publication. Ganesan, K., Thompson, A., Smid, C., Cañigueral, R., Kievit, R. A., & Steinbeis, N. (in prep) Effects of cognitive control training on executive function factors.

4.1. Abstract

Executive function training has received immense interest, given its role in supporting later wellbeing and positive outcomes. Typically, training interventions target a particular executive function to test whether transfer to other executive functions occurs. Whether it does so and to what extent is however unclear. Further, while studies typically sum indices of error rates and reaction times, examining them separately could give us more insight into executive function training. Here we focus on inhibition as a training mechanism, using a randomized-control trial with a highly variable, adaptive and complex gamified training protocol in a highly-powered sample of 235 children aged 6-12 years. While no improvements in error rates of executive functions were found, increases in strategic slowing (yielded from a factor analysis using all measures) was observed in the experimental group. Our findings highlight the necessity for executive function training studies to examine error rates and speed separately. While our findings show promise for inhibition-based training, future research is necessary in assessing the maintenance of improvements.

4.2. Introduction

Executive functions (EFs) help support flexible goal-directed behaviours and thought (Botvinick & Braver, 2015; Diamond, 2013), through stopping of pre-potent responses and impulses (inhibition), manipulating and remembering goal-related information (working memory) and responding flexibly to changes in the environments (shifting). Indeed, EFs have been predictive of later success and wellbeing with clinically relevant behaviours such as attention-deficit hyperactivity disorder (ADHD) characterised by EF deficits (Metin et al., 2012; Moffitt et al., 2011; Willcutt et al., 2005). Therefore, there has been great interest to train EFs with the aim to improve positive real-world outcomes (Diamond & Ling, 2016, 2019). In chapter 3, we show that inhibition had a privileged role (as compared to context monitoring) as a target mechanism for training interventions. Training typically comprises of interventions using a specific task to train a specific mechanism (i.e. inhibition training through a SSRT task in Chapter 3). In this chapter, we investigate if improvements extend to other EFs (i.e. memory, shifting).

The unity and diversity model indicates that EF primarily consists of three separable factors: inhibition, working memory and shifting. Although separable to some degree, these factors are said to share commonality (Tirapu-Ustárroz et al., 2017; Wu et al., 2011). Indeed, this is mirrored by neural data suggesting that overlapping yet separable neural substrates underlie EF functions (Bettcher et al., 2016; Fiske & Holmboe, 2019; McKenna et al., 2017). Further, multi-measurement studies lend support to the unity and diversity account, with factor analysis yielding multiple factors of EF (Huizinga et al., 2006; Karr et al., 2018; Messer et al., 2018, 2022).

Therefore, by training inhibition, we would expect transfer to other EFs given their overlap in neural circuitry which may indicate a common mechanism underlying all EFs (McKenna et al., 2017). Inhibition in particular has been posed to represent common executive functioning (Aron et al., 2007; McKenna et al., 2017). Therefore training inhibition should tap into a shared mechanism underlying EFs and transfer to the other EFs should be observed. Indeed, inhibition may be highly relevant to a wide set of processes including response selection, context monitoring and attentional control (Bari et al., 2020; Chatham et al., 2012; Mackie et al., 2013; Wodka et al., 2007) as well as being core to clinically relevant behaviours characterised by EF deficits such as ADHD and OCD (Blair & Razza, 2007; Mar et al., 2022; Wodka et al., 2007). Inhibition has been posited to serve as a fundamental pillar of executive functioning, being the first EF to emerge, and has been reported to develop as early as 6 months old (Hendry et al., 2022; Holmboe et al., 2008). In line with this, one meta-analysis found that inhibition-related neural activity completely overlapped with general executive functioning related activity (McKenna et al., 2017) a finding supported by Chapter 2. Indeed, for example with shifting, we could argue that in order for another task to be pursued, the current task at hand has to be 'inhibited' (Chevalier et al., 2014; Chevalier & Blaye, 2009). These findings taken together suggest that transfer to other EFs should occur due to the organisation of EFs. Training inhibition, in particular, should result in transfer to other EFs.

However, the evidence of transfer to other EFs is mixed. A meta-analysis looking at working memory training found that training did not successfully lead to improvements in inhibition (Sala & Gobet, 2017). Similarly, shifting-based training did not lead to successful changes in an untrained inhibition task (Podlesek et al., 2021). Perhaps, working-memory and shifting training do not successfully tap into a general shared mechanism that underlie EF. Therefore, training might simply work on improving a specific skill (e.g., working memory in a n-back task, flexibility in a flanker shifting task) rather than improving EFs more broadly. As suggested, inhibition-based training may hold promise given that it may tap into a mechanism underlying EFs generally (Kubota et al., 2020; but see also Podlesek et al., 2021).

Part of the mixed evidence could be potentially attributed to task impurity. Instead of measuring if training is transferring into shifting abilities, studies are actually looking at whether it is transferring into indices relating to a specific task (Snyder et al., 2015). While these tasks may primarily depend on EF abilities, they may be confounded by other abilities such as comprehension abilities. This could explain the mixed evidence on training-related changes in EFs (Podlesek et al., 2021; Sala & Gobet, 2017). Therefore, a multi-measurement approach is necessary in assessing changes in EFs. Another explanation could be that current training interventions are poor and unsuitable for children. As utilizing EFs is effortful, it is necessary for engagement and motivation with training designs to be high (Botvinick & Braver, 2015; Johann & Karbach, 2020; Smid et al., 2020). Therefore, designing a gamified training protocol is necessary to maximise training gains.

In EF tasks, measures of both error rates and reaction times are collected (Bakun Emesh et al., 2022; Messer et al., 2018, 2022). Often these measures are summed to calculate a composite score (Bakun Emesh et al., 2022). Specifically, cost of performance is calculated by summing error rates and reaction times. Particularly with inhibition and shifting tasks, these are relative scores. For example, in a cognitive flexibility task, both stay and switch trials are administered (Karbach & Kray, 2009). Therefore, the cost of shifting is calculated as the relative cost of performing switch trials vs stay trials (Friedman, 2016; Messer et al., 2018). Often, increased cost is interpreted as worse performance (i.e. better EF abilities – lower error rates and reaction times). However, this is inconsistently conceptualised in the literature, with the main disagreement lying with the conceptualisation of reaction times (Bellon et al., 2019; Gärtner et al., 2021). This may also suggest why some studies examine error rates solely as proxy for performance (Messer et al., 2022; Scionti & Marzocchi, 2021; Völter et al., 2022). Despite this, reaction times could provide fine-grained information about children's behaviour that error rates may not be able to capture (de Boeck & Jeon, 2019).

While higher reaction times have been conceptualised to represent poorer performance in EF studies, increased reaction times (i.e. slowing) could potentially aid and help improve accuracy in EF tasks (Bruyer & Brysbaert, 2011; Hedge et al., 2019). Higher reaction times could indicate a more cautious strategy to minimise errors (Hedge et al., 2018; Miller & Ulrich, 2013). This possibility questions the basis of current studies employing composite measures of error rates and reaction times. In fact, although composite measures help with measurement validity, error rates and reaction times could represent different processes that underlie behaviour. This is supported by the inconsistency observed in the relationship between speed and accuracy in the literature (Domingue et al., 2022; Williams et al., 2007). In the context of our inhibition-based training, examining reaction times and accuracy separately may allow us to disentangle the exact mechanism that may be trained.

In sum, using a multi-measurement and factor analysis approach, we examined how an inhibition-based training can produce transfer to other EFs. For this, we used a well-powered, rigorous double-blind randomised controlled trial

(RCT), leveraging a highly motivating gamified interface and maximal variation of training contexts and mechanisms. Crucially, we ensured optimal adaptiveness of the training protocol by means of a trial-by-trial adaptation (using a staircase procedure) based on performance, ensuring that trials were scaled appropriately to individual's cognitive control abilities.

We set out to test whether training-related changes in error rates and reaction times of executive function tasks is observed. We examine whether changes in reaction times predict changes in error rates. Finally, we look at whether maintenance of training-related changes are observed at 1-year follow-up.

4.3. Materials and Methods

4.3.1. Participants

A total of 262 typically developing children were recruited for the study (6.03-13.31 years; Age M = 8.97 years, Females = 52.84%) from schools within Greater London in the United Kingdom (data collection started in May 2019 and ended in May 2021). Parental consent was obtained beforehand and the study was approved by the University College London research ethics committee (Protocol number: 12271/001). In accordance with this, written consent was obtained from both parents and children after providing a description of the study. Socioeconomic status was assessed based on employment and education of both parents (Supplementary Materials Table S5-1). There was a positive skew in SES (M = 1.64; on a scale of 1-5, where 1 is the highest score attainable). Ethnic composition of our sample was as follows: Asian = 14.65%; Black = 3.18%; Mixed/multiple ethnic groups = 17.20%; White = 64.33%; Other = 0.63%). There were no specific exclusion criteria.

4.3.2. Study Design

There were 4 main phases to the study. After an initial baseline data collection phase at pre-test (T0), the 8-week computerised intervention was administered. This was followed up by a post-test (T1) and finally, a 1-year-follow-up (T2). Executive function measures (i.e. at pre-test, post-test, 1-year-follow-up) were collected to examine independent near- and far-transfer changes. Due to disruptions to in-person testing during the Covid-19 pandemic, a subset of tasks were moved and collected online. More details on the datapoints for each individual task have been provided (Supplementary Materials Table S4-1).

4.3.3. Training

Training was presented in the form of a computerised web-based Treasure Game. The training was designed to last 8 weeks, with four recommended sessions per week, one taking place at school and three at home. Each session was programmed to take approximately 15 minutes. Both groups received identical training in terms of narrative, stimuli and intensity. The only difference between the groups was how participants were instructed to respond to the stop stimuli (i.e. inhibit for the experimental group and respond for the control group).

4.3.3.1. Experimental Group: Inhibition Training

To train inhibition a stop signal response task was used. Participants were instructed to press the spacebar on presentation of a ‘go’ signal. On stop trials where a ‘stop’ signal appeared after the ‘go’ signal, participants were instructed to inhibit pressing the spacebar. ‘Go’ and ‘stop’ signal stimuli and inhibition mechanism varied according to the game being played. The stop signal delay (SSD) was initially set at

200ms. After successful inhibition, the SSD would decrease by 50ms and after failed inhibition, it would increase by 50ms (Logan, 1997; Verbruggen & Logan, 2009). This ensured that the training was adaptive. Stop trials occurred 26-47% for each training session. To ensure adaptiveness across training sessions, the SSD of each subsequent session was taken from the final ‘stop’ trial of the preceding session on that specific training game.

4.3.3.2. Control Group: Response Speed Training

The response speed training was identical to the experimental condition in all aspects except that a response was required for all signals. Participants were instructed to press the spacebar as quickly as possible. To ensure that training was adaptive for this group, participants had to respond within a time window that was set based on a rolling average of the response time of the previous ten trials plus two standard deviations. This ensured that the training was adaptive, while minimising the effect of outliers on the response threshold.

4.3.4. Pre-post Executive Function Tasks

A total of 9 executive function tasks were collected, assessing different functions (i.e. inhibition, shifting, and working memory). Visual designs of these tasks have been shown in Supplementary Figure 1-8. For all tasks, participants were presented with practice trials before main trials were administered, where they had to attain a criterion threshold for accuracy. Additionally, comprehension questions were employed to ensure participants understood the rules for each task (e.g. ‘What button should you press if you see a bear on the screen?’). Rules were re-explained if participants answered incorrectly on any of the questions. The experimenter noted if the participant still failed to comprehend the task. All participants managed to pass these comprehension questions; therefore, no individual was excluded from the analysis. The task was presented using the software Presentation (www.neurobs.com; Version 23). When the Covid-19 pandemic occurred, a subset of executive function tasks were administered online via Gorilla (www.gorilla.sc) during remote testing (A. Anwyl-Irvine et al., 2021; A. L. Anwyl-Irvine et al., 2020).

4.3.4.1. Inhibition Tasks

Stop-Signal Reaction Time Task. A measure of cognitive control was administered via a child-friendly version of the SSRT (Matzke et al., 2018). Ten practice trials were administered before 80 trials of the main task. Each trial started with the presentation of a fixation cross of 1250ms. During the task, participants were asked to press the left arrow key when seeing the ‘go’ signal (i.e. a honey pot) on the left side of the screen and the down arrow key when the signal appeared on the right side. On 25% of the trials (i.e. a ‘stop’ trial), a picture of bees was presented after the honey pot. This served as the ‘stop’ signal. The stop signal delay (SSD) started at 200ms, decreased by 50ms after a successful ‘stop’ trial, and increased by 50ms after an unsuccessful ‘stop’ trial. As a measure of inhibition, a mean SSRT (ms) was calculated using the integration method (Verbruggen et al., 2019). Several studies have validated the SSRT as a measure of response inhibition (Logan et al., 2014) and it is correlated with self-report measures of impulsive behaviours in young adults (Logan, 1997).

Flanker Inhibition. The participants completed a child-friendly version of the Eriksen Flanker inhibition task (Eriksen and Eriksen, 1974). Children were presented with a row of fish on the screen. They were required to focus on the fish in the centre (named Chloe) and indicate the direction in which it was swimming (i.e. left key response required when the fish was facing left; down key response required when the fish was facing right). Participants were told to ignore the direction other fish swim in and only indicate the direction Chloe swam in. On congruent trials, all fish faced the same direction. On incongruent trials, surrounding fish faced the opposite direction to Chloe. Fish were presented for 700ms before they disappeared. Participants were given a maximum of 2500ms to respond from stimulus onset. A total of 20 congruent trials and 20 incongruent trials were administered. This task was chosen because it is a child-friendly task for ages six years and up and has been validated in several studies (McDermott et al., 2007; Mullane et al., 2009). The difference in both reaction times and error rates between incongruent trials and congruent trials was calculated separately.

Stroop. Participants completed a child-friendly version of the Stroop task (Williams et al., 2007). The task was introduced as the ‘Farm Animal’ game, where they were told to match animals to their homes (e.g. dog to a kennel). They were presented with both auditory stimuli of an animal sound (e.g. ‘bark’, ‘meow’, ‘croak’ for a dog, cat, and frog, respectively) and visual stimuli of the animals. Crucially, participants were asked to match animals to where they live (e.g. frog to a pond). They were told to listen carefully to an auditory cue indicating the animal type (e.g. frog – ‘ribbit’) and not to pay attention to the visual cue of the animal presented on the screen. Trials lasted for 10000ms within which participants had to make a response. While audio stimuli was presented for 600ms, visual stimuli was presented until participants made a response (max of 1000ms). A blank screen with a ‘cross’ was presented between trials for 10000ms (ITI). On congruent trials, both auditory and visual cues matched (e.g. frog presented on screen and ‘ribbit’ tone played). On incongruent trials, auditory and visual cues did not match (i.e. dog presented on screen and ‘ribbit’ tone played). Participants completed 72 trials in total, with 36 congruent and 36 incongruent trials. The differences in both reaction times and error rates between incongruent trials and congruent trials were calculated separately.

4.3.4.2. Memory Tasks

N-back. Both the 1-back and 2-back tasks were administered to measure working memory (Chen et al., 2008). The task was adapted to be child-friendly and introduced as the ‘Dino-Donut’ game, where participants were told that dinosaurs were lining up to eat some donuts. For the 1-back task, they were told to stop dinosaurs that tried to eat a donut twice in a row and to press the spacebar if they appeared consecutively to stop them. For the 2-back task, they were told that the dinosaurs became sneakier, and this time they should press the spacebar if the same dinosaur appeared two trials prior. Stimuli were shown for 500ms followed by a 1500ms Inter-Stimulus-Interval (ISI). Responses had to be made before the onset of the next stimulus presentation. Participants completed 80 trials in total, 40 for each n-back condition. As a measure of error rate, false alarm rate was calculated for both 1-back and 2-back tasks. Reaction times to make a correct response was also calculated.

Corsi block-tapping task. Working memory span was assessed using the Corsi block-tapping task, which measures visuo-spatial working memory span with a higher value indicating a higher working memory span (Farrell Pagulayan et al., 2006). This task consisted of ‘Freddy the frog’ jumping between nine potential locations designed as lily pads. The participants followed the jumps by clicking on the lily pads in a forward sequence. Trials commenced with a count-down from three to one to alert participants to the start of a trial. Then the stimulus of the frog jumping was shown for 600ms for every jump. The ISI was fixed to 600ms. Participants completed three practice trials with feedback and there was a total of 14 main trials. Initially, participants had to remember and click on two lily pads. The task employed an adaptive staircase design where the working memory load (i.e. number of lily pads to remember) increased by one when participants made two consecutive correct answers. The maximum working memory load attained was used as a working memory span measure.

4.3.4.3. Shifting Tasks

Cognitive Flexibility. A child-friendly version of the cognitive flexibility task assessed participants' ability for rule switching across dimensions (using sound cues: ‘animal’ or ‘size’). If a sound cue of ‘animal’ was played, participants had to indicate if the animal was a cat or dog. If a sound cue of ‘size’ was played, participants had to indicate whether the animal observed was small or large (Karbach & Kray, 2009). Participants had 10 seconds to respond before the trial timed out, during which the stimuli remained on the screen. Responses made before 200ms after stimulus onset were not recorded. The inter-trial interval (ITI) was jittered and ranged from 1000ms to 1200ms. Stay trials were preceded by a trial with the same rule (e.g. deciding on the type of animal was presented twice in a row). During switch trials, the current trial was preceded by a trial in a different dimension (i.e., participants had to first respond to the size of the animal and then to the type of animal that is presented). Following a practice block, participants completed 40 trials (consisting of 28 stay trials and 12 switch trials). Participants completed 20 single-dimension trials in two blocks and 40 mixed trials in one block. The difference in reaction times between switch trials and stay trials was calculated.

Flanker Shifting. The participants completed a child-friendly version of the Eriksen Flanker shifting task (Karbach & Kray, 2009). Children were presented with a row of fish on the screen. They were told that all the fish swim in the same direction. However, that two colours of fish would appear: orange and purple fish. When orange fish were presented, they were instructed to indicate the direction in which the fish swam (i.e. left key response required when the fish faced left; down key response required when the fish faced right). When purple fish were presented, they were instructed to indicate the opposite direction in which the fish swam (i.e. left key response required when the fish was facing right; down key response required when the fish was facing left). Fish were presented for 700ms before they disappeared. Participants were given a maximum of 2500ms to respond from stimulus onset. Stay trials were defined as those where the rule for the previous trial was the same as the current trial (i.e. purple trial following a purple trial; orange trial following an orange trial). Switch trials were defined as those where a rule change has occurred (i.e. purple trial following an orange trial; orange trial following a purple trial). Based on this, there were 28 stay trials and 12 switch trials. The difference in both reaction times and error rates between switch trials and stay trials was calculated.

4.3.4.4. Complex EF Tasks.

AX-CPT. Reactive and proactive control were measured using a child-friendly version of the AX-CPT paradigm (Chatham et al., 2009). The task was introduced as the Fruit Island game. An ‘A’ or ‘B’ cue (i.e. dog or cat) was presented in the middle of the screen for 500ms, followed by an inter-stimulus interval of 750ms and then a probe ‘X’ or ‘Y’ (orange or apple) during which participants had to make their response. Participants were instructed to press the left key whenever an ‘X’ followed an ‘A’ (i.e. AX trials) and to press the down arrow key for all other cue-probe combinations. Importantly, they were instructed to only respond once the probe had been presented and were alerted of this if they made a response before the probe was presented. Participants had a maximum of 6000ms to make a response. Responses were followed by an inter-trial interval of 1500ms. The proportions of the trial types were based on previous studies (Chatham et al., 2009; Richmond et al., 2015) where 40% of trials were AX trials. All other trials (i.e. AY, BX, BY trials) were presented 20% each. Trials were presented randomly. Ten practice trials were administered where feedback was provided, followed by 60 main trials. Proactive control index (PBI) was calculated for error rates and reaction times separately (Braver et al., 2009).

4.3.5. Statistical Analysis

4.3.5.1. Validation Checks

Where possible validation checks were performed at T0 for all measures of executive functions to examine if patterns were consistent (Supplementary Materials Figures 9-14). Specifically, differences in error rates and reaction times were examined between the conditions/trials. This was not possible for the SSRT and Corsi Block Tapping Task. For the n-back tasks, indices across the 1-back and 2-back tasks were compared (Supplementary Materials Figures 13).

4.3.5.2. Executive Function factors

Outliers were removed from behavioural executive function measures. Datapoints falling two standard deviations below or above the mean were excluded. Then, a confirmatory factor analysis (CFA) was performed using lavaan in Rstudio to create latent factors of EFs (Rosseel, 2012). For the error rate factor specifically, inclusion of flanker inhibition indices caused non-convergence of models and was excluded from analysis. Based on previous literature, factor loadings were constrained by timepoints to allow for pre-post comparisons establishing weak factorial invariance (Judd & Klingberg, 2021; Moura et al., 2018). Values for each individual were extracted from this for further analysis. This was done separately for error rates and reaction times, where a bigger value indicated a bigger error rate or reaction time.

4.3.5.3. Training-related changes

Mixed models were used to examine training-related changes. In this model, the main effects of training group and session were examined as well as the interaction between group and session. Age was added into the model as a covariate. Significant interaction effects between Session and Group were interpreted as presence of training-related changes and followed up with post-hoc paired t-tests.

In a subset of available tasks, maintenance of training-related changes were examined between pre-test (T0) and 1-year follow-up (T2). Composite measures of tasks were used for this.

4.3.5.4. Relationships between error rates and reaction times

Regression models were employed to examine how the factor of reaction time predict factors of error rate. In this model, age was added as a covariate.

4.3.5.5. Data imputation

Multiple Imputations by Chained equations (MICE) was used to impute missing data (predictive mean matching; iterations = 20, *N* datasets = 100). A single imputed dataset was used as this was necessary in conducting mixed models with post-hoc tests and factor analysis. We ensured the replicability of these results by re-running the process multiple times and choosing a dataset at random.

4.4 Results

4.4.1. Training Indices

Training took place over an 8-week period. The motivation to train was high to begin with (Experimental Group = 5.30; Control Group = 5.30; rating 1-7) and decreased as training went on (*F* (6, 308.75) = 16.42, *p* < .001; Figure 4-1a). There were no group differences in overall motivation between groups (BF_{10} = 0.23; *t* (395.13) = -0.50, *p* = .61; Figure 1a), nor an interaction between Session and Group (*F* (6,308.75) = 1.45, *P* = .194). On average, individuals in both groups trained a similar number of sessions (Experimental Group: 16.60; Control Group: *N* = 16.99). There was no significant difference in the amount trained between the two groups (BF_{10}= 0.16; *t* (205.33) = 0.33, *p* > .740; Figure 1b). To assess whether each group improved on the trained cognitive function throughout the training, we examined changes over the training sessions in the SSRT (Experimental Group) and Go RT (Control Group) respectively. For this, we looked at the slope of change in these trained cognitive functions using a mixed model with training weeks added as a predictor. There was a main effect of session where both groups improved on their trained cognitive functions over the training weeks (Experimental Group: *F* (1, 2292.60) = 121.30, *p* < .001; Control Group: *F* (1, 3197.5) = 185.57, *p* < .001; Figure 1c). Thus, the groups did not differ in training intensity or motivation and showed improvements during training in the targeted processes.

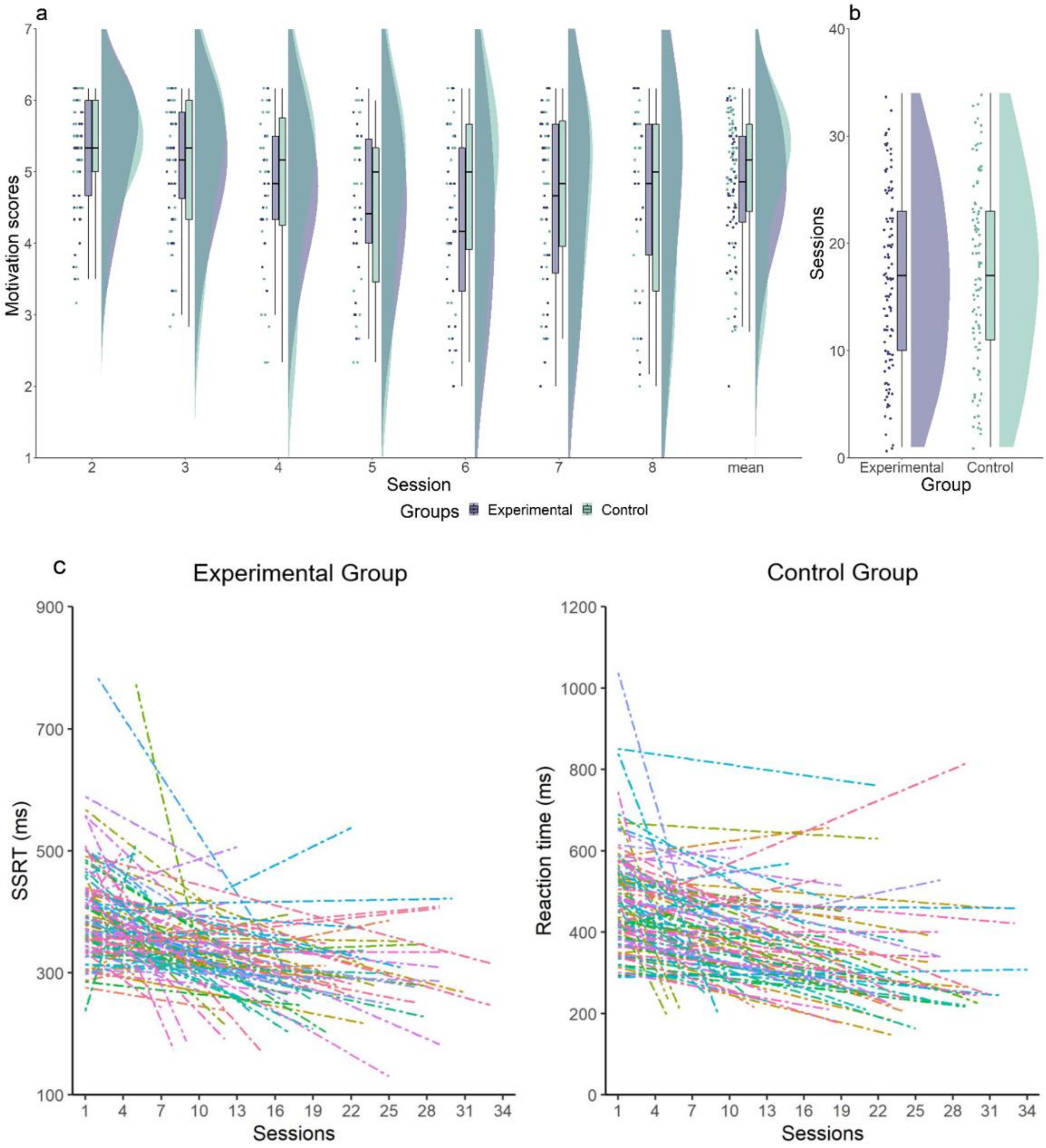


Figure 4-1. Training-related indices showing that (a) Motivation in both groups was comparable. (b) Comparable number of sessions performed by both groups. (c) Lines reflect individuals in the Experimental and Control group where improvements in respective domains as a function of training were observed. Both groups improved in their respective domains as a function of training.

4.4.2. **Error Rates (%)**

Factor fit. A two-factor structure fit best for both timepoints. This structure was a better fit than a three-factor structure model. In this structure, inhibition and shifting measures loaded onto the first factor with memory measures loading onto the second factor (Figure 4-2).

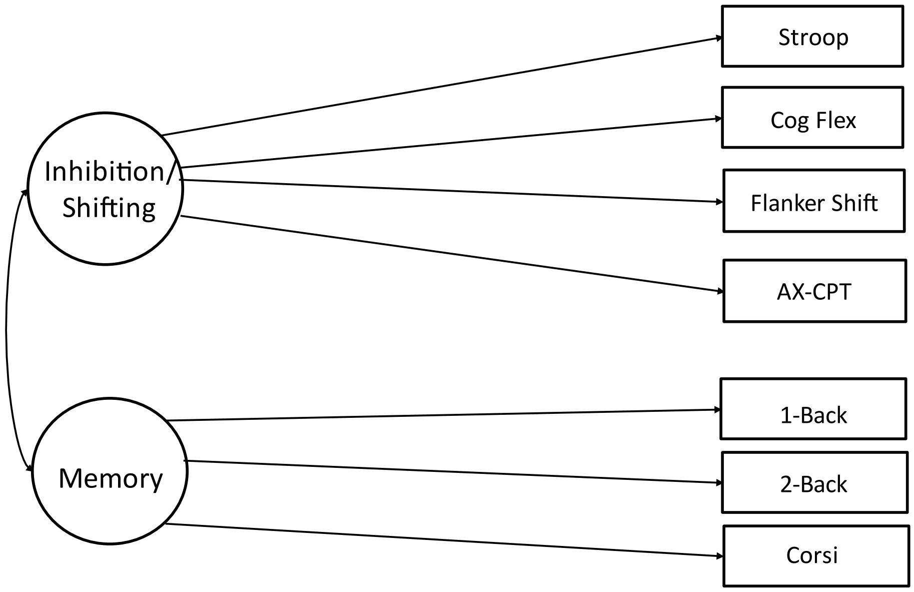


Figure 4-2. Factor analysis revealed a two-factor fit for error rate measures of executive functions.

Training effects. There was no group and time interaction found with the inhibition/shifting factor (*F* (1, 213.34) = 0.00, *p* = .999; Figure 4-3a) nor the memory factor (*F* (1, 203.06) = 1.08, *p* = .299; Figure 3b).

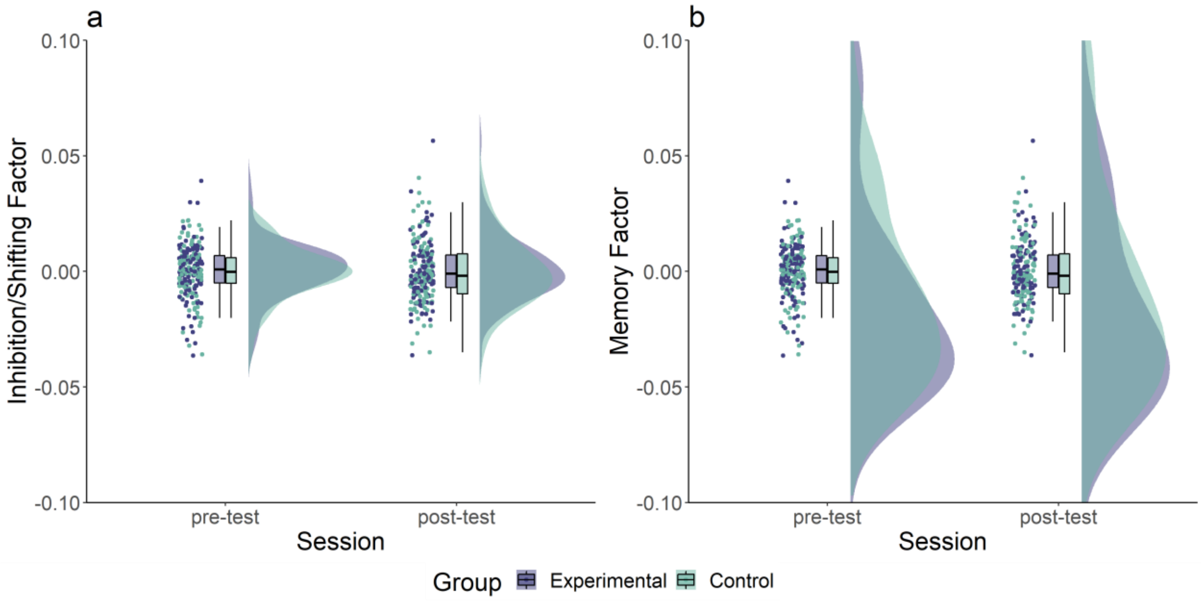


Figure 4-3. No training-related changes found in factors of (a) inhibition/shifting and (b) memory, based on error rates (%).

4.4.3. Reaction times

Factor fit. A one-factor structure fit well for both timepoints. In this structure, all measurements of inhibition, shifting, and memory loaded onto a unitary factor (Figure 4-4). We note all other models failed to converge (i.e. 2-factor, 3-factor) and therefore, we are unable to perform any comparisons on model fit.

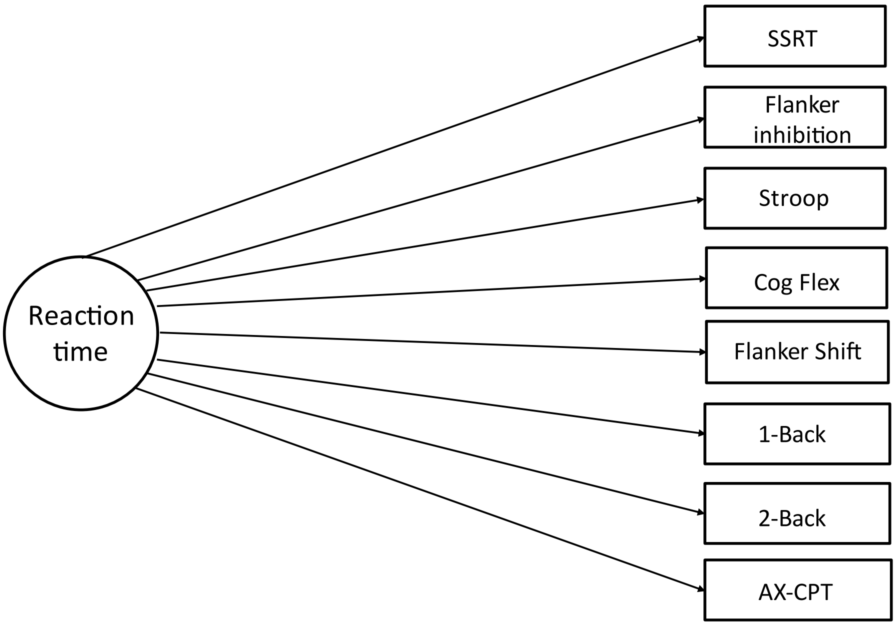


Figure 4-4. Factor analysis revealed a unitary fit for reaction time measures of executive functions.

Training effects. There was a significant group and time interaction found in the unitary reaction time factor (*F* (1,210.68) = 18.60, *p* <0.001). Pre-post test comparisons in the experimental group revealed increases in the unitary reaction time factor, indicating increases in reaction time (*t* (103) = -3.07, *p* = .003; Figure 5). In the control group, decreases in the unitary reaction time factor were found, indicating decreases in reaction time (*t* (100) = 2.93 *p* = .004; Figure 4-5).

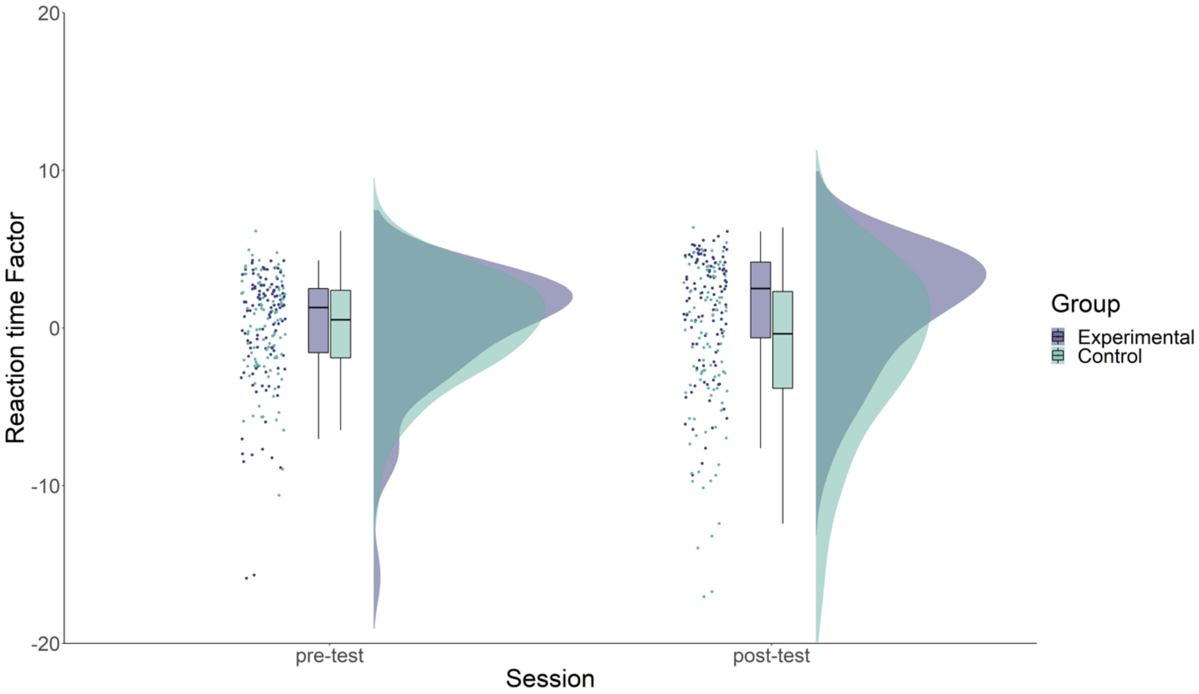


Figure 4-5. Increases in the reaction time factor was found in the experimental group while decreases in the reaction time factor was found in the control group.

4.4.4. **How do reaction times predict error rates?**

We examined how changes in reaction times may predict changes in error rates. In the experimental group changes in reaction times did not predict changes in any of the error rates of our executive function factors (Inhibition/shifting factor: *t* (101) = -0.93, *p* = .353; Memory factor: *t* (101) = 1.07, *p* = .286; Figure 4-6). Similarly, in the control group changes in reaction times did not predict changes in any of the error rates of our executive function factors (Inhibition/shifting factor: *t* (98) = 0.30, *p* = .768; Memory factor: *t* (98) = -0.81, *p* = .420; Figure 4-6).

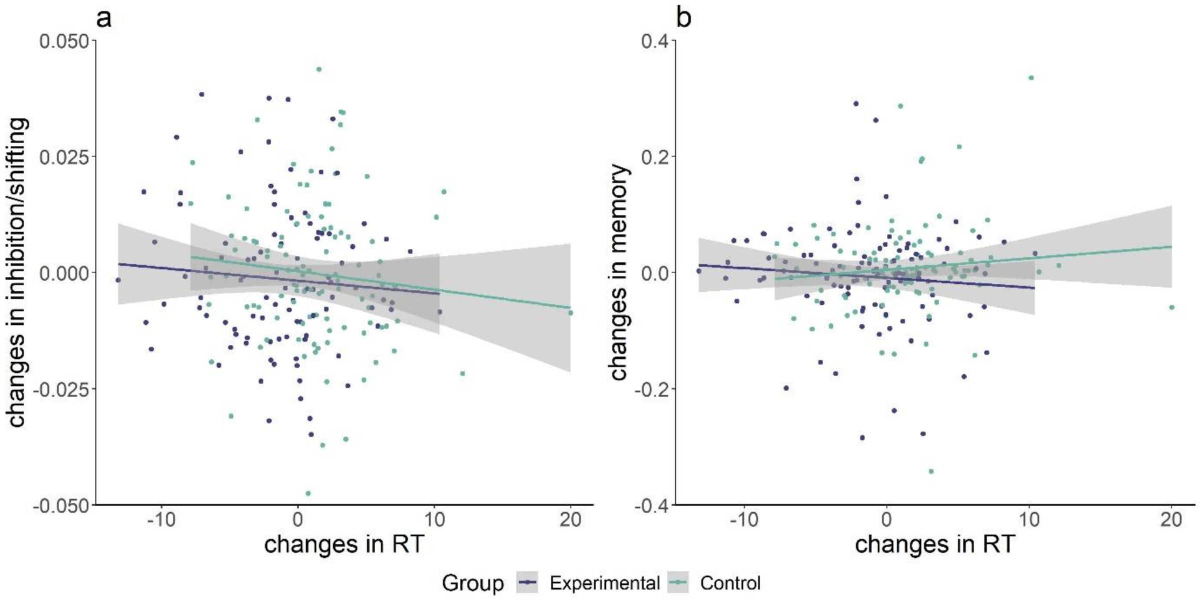


Figure 6. Changes in reaction time did not predict changes in either factor based on error rate of (a) inhibition/shifting or (b) memory.

4.4.5. **Maintenance of training effects**

We looked at maintenance of training effects at 1-year follow-up in a subset of tasks (i.e. SSRT, Cognitive Flexibility, Corsi Block Tapping, AX-CPT). Only for our measure of SSRT were training effects sustained. A mixed model revealed a significant interaction between Session and Group in SSRT scores (*F* (1, 233.49) = 4.15, *p* = .043). Follow-up paired t-tests indicated that these improvements were sustained at a 1-year follow-up as indicated by direct comparison of pre-test and 1-year follow-up (*t* (225) = 4.90, *p* < .001). Follow-up paired t-tests in the control group revealed no significant differences between pre-test and 1-year follow-up (*t* (223) = 0.65, *p* = .278). A significant interaction between Session and Group in mean Go RT was observed (*F* (2, 444.59) = 8.39, *p* = .016). This interaction was still significant after controlling for age (*F* (2,440.01) = 8.67, *p* = .011). Follow-up paired t-tests revealed that increases in reaction times were sustained at 1-year follow-up (t (228)

= 5.97, *p* < .001, d = -.57; Figure 4-3b). In the control group, change was not sustained at 1-year follow up (t (225) =1.98, P = .297, d = -.17; Figure 4-7b).

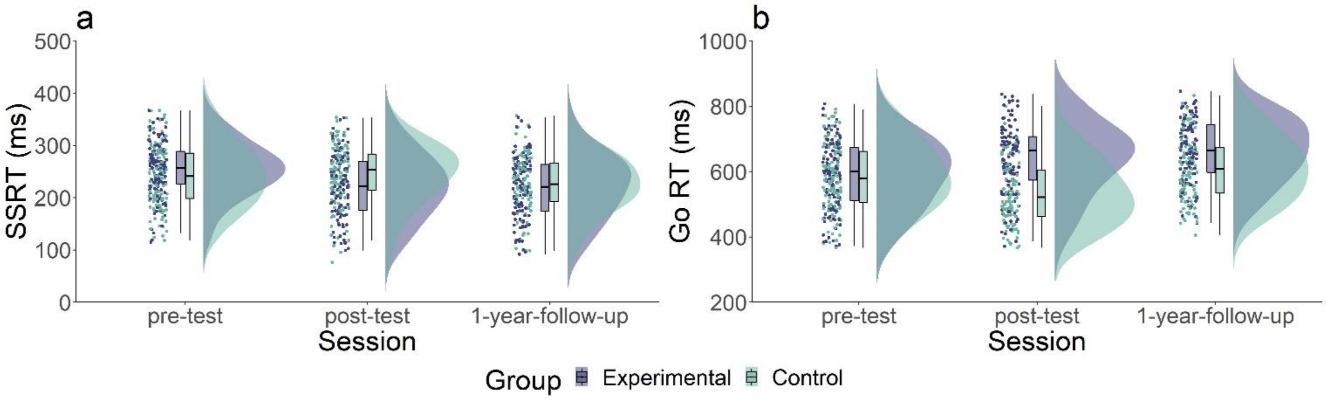


Figure 4-7. (a) Training related improvements in SSRT scores observed for experimental group from pre- to post-training, which are maintained at 1-year follow-up. (b) Training-related slowing of responses for experimental group from pre- to post-training, which are maintained at 1-year follow-up.

For all other executive functions, no maintenance of training effects were found in either measures of error rates or reaction time. No significant Session and Group interaction were found in the indices of the cognitive flexibility task (*F* < 0.17, *p* > .682). Corsi block tapping (*F* < 2.31, *p* > .130) or the AX-CPT (*F* < 1.40, *p* > .237).

4.5. Discussion

Chapter 4 used a multi-measurement approach to executive functions in investigating the extent to which transfer could occur through inhibition training. Further, we investigated this by examining reaction times and error rates separately, hypothesising that this approach could give us more fine-grained understanding to EF training. We find no training-related improvements in error rates. Conversely, increases in the reaction time factor were found in the experimental group. This points to inhibition-based training generally training children on a strategy of slowing.

However, we note that this strategic braking did not predict improvements in error rates.

In our study, we used an inhibition-based adaptive and gamified training protocol to examine changes in EFs. We aimed to clarify inconsistent training effects by using a multi-measurement approach to examine EFs. Motivation was high in both groups ruling out any training design related differences in the groups that may have contributed to training-related changes. Both groups performed an equal number of sessions and showed comparable improvements on their targeted cognitive functions as indicated by changes during the training sessions. Our intervention design therefore ensured optimal conditions for learning and generalisation (Raviv et al., 2022; Smid et al., 2020) and more importantly, highly comparable engagement and improvement in targeted functions for both training groups. This is an ideal starting point from which to interpret any group differences in training outcomes.

Given the inconsistency in previous literature on speed-accuracy trade-offs (Domingue et al., 2022), we examined training-related improvements in error rates and reaction times separately. Additionally, in the context of the training task, where children in the experimental group are required to monitor for a ‘stop’ signal while children in the control group are trained to speed up their responses. Therefore, examining error rates and reaction times separately could give us further insight into the exact mechanism and processes that our training tapped into. Indeed, we find different patterns between measures of error rates and reaction times.

For error rates, a 2-factor fit our data best (i.e. inhibition/shifting factor and memory factor). This is line with previous literature examining EFs in a similar age group (Huizinga et al., 2006; Karr et al., 2018; Messer et al., 2018, 2022). However, we note that no training-related changes were observed in either factor based on error rate. This may suggest that our gold-standard protocol was unable to improve error rates amongst other EFs. When looking at indices of reaction times, a unitary factor was yielded. This points to a singular construct of strategic slowing amongst all functions of EF (i.e. common mechanism underlying EFs). In line with this, we find training-related pre-post increases in strategic slowing. Indeed, Chapter 3 suggests that inhibition training produced transfer into proactive control (i.e. adaptive slowing of responses). However, we do note that these increases in reaction times did not drive improvements in error rates.

This could be partially attributed to the setup of our tasks. Generally, for some of the EF tasks, fast responses were required. Therefore, the strategy of slowing down to increase accuracy may not have been a beneficial one. Indeed, we found varying patterns of speed-accuracy trade-offs in our tasks (Supplementary Materials Table S4-2). For instance, while the n-back (i.e. 2-back) task showed a negative relationship between speed and accuracy (i.e. slower responses leading to better accuracy), the flanker inhibition task and 1-back task showed a negative relationship between speed and accuracy (i.e. faster responses leading to better accuracy). This suggests that task complexity or difficulty could play a role in determining if strategic slowing is an adaptive strategy (i.e. leading to better accuracy). In particular, our findings suggest that a more challenging task may benefit from strategic slowing where arguably slowing down to careful consider the response that should be given helps improve accuracy. We note that for all the other tasks no relationship between speed and accuracy was found. This is in line with previous literature finding inconsistent or no relationships between the two domains

(Domingue et al., 2022). Though arguably this slowing ability may translate to other domains of far transfer/real-world transfer rather than task-related accuracy. For instance, in a real-world context, such slowing could support proactive control in the maintenance of task-relevant information in preparation of response execution (Braver, 2012). Indeed, a paper found that such slowing is associated with better lexical and arithmetic accuracy (Domingue et al., 2022). However, a similar issue arises here, where the relationship between speed and real-world outcomes is inconsistent. For instance, no links between speed and domains of health were observed (Domingue et al., 2022). However, we note that this study examined reaction times, rather than strategic slowing (i.e. slowing on a more complex/mentally demanding task vs less complex task). Speed may also be heavily confounded with variables such as age and IQ (Der & Deary, 2017). Additionally, longer responses may be associated with mind wandering and lapses in attention which could contribute to increases in error rates (Gmehlin et al., 2016; Smallwood & Schooler, 2015). This makes establishing the precise role of strategic slowing difficult. Therefore, future research needs to carefully consider this in disentangling the role that strategic slowing could play in predicting real-world outcomes.

Finally, apart from the SSRT Task (i.e. similar to training task), we note that maintenance of training-related effects were not found. This highlights and reinforces that maintenance of training-related gains is still a problem even with a gold-standard design (Holmes et al., 2009; Johann & Karbach, 2020). However, we note our limitations in accurately assessing sustained training changes. Due to Covid-19, we were unable to move testing online for all the executive function tasks, therefore we are unable to comment on the maintenance of training effects well. We have reported the maintenance effects for the individual tasks, however these could easily be confounded by task-impurity issues. Ideally, we would have been able to conduct a factor analysis for all three timepoints.

In conclusion, while we find training-related strategic slowing in the experimental group, these changes do not predict improvements in error rates. Our findings highlight the necessity for examining indices of error rates and reaction times separately. While these findings are promising for inhibition-based training interventions, future research needs to examine more clearly the maintenance of training-related improvements.

4.6. Supplementary Materials-4

Tasks	**T0**	**T1**	**T2**
SSRT	226	162	164
AX-CPT	232	154	159
Stroop *	194	83	-
Flanker Inhibition *	190	87	-
Flanker Shifting *	188	82	-
Cog Flex	215	140	146
1-back *	196	84	-
2-back *	196	84	-
Corsi	230	135	156

Table S4-1. Number of datapoints for each task at each timepoint.

Tasks	**Correlation between error rates and reaction times (*r*)**
AX-CPT	.04
Stroop	.08
Flanker Inhibition	.13
Flanker Shifting	-.03
Cog Flex	-.07
1-back	.15
2-back	-.17

Table S4-2. Correlations between error rates and reaction times for each task

Note: Significant correlations (*p* < .05) have been bolded. A positive correlation suggests that higher reaction times are associated with higher error rates. A negative correlation suggests that higher reaction times are associated with lower error rates.

Chapter 5. Far-transfer of a real-world outcome through cognitive control training

Part of Chapter 5 has been written in preparation for publication with a preprint available. Ganesan, K., Cañigueral, R., Thompson, A., Smid, C., Puetz, V., Kievit, R. A., & Steinbeis, N. (submitted) Training cognitive control in middle childhood impacts attentional control preprint: https://psyarxiv.com/spzjn

5.1. Abstract

Children’s performance on cognitive control tasks predicts a range of real-world outcomes, and has been a primary target for interventions. Such interventions rarely impact other domains (i.e. far transfer), however this may be masked by methodological shortcomings and poorly specified mechanisms of action. Here we focus on a well understood but rarely targeted facet of cognitive control, namely inhibition, using a randomized-control trial with a highly variable, adaptive and complex gamified training protocol in a highly-powered sample of 235 children aged 6-12 years. We found sustained training-related changes in cognitive control as well as improvements in real-world assays of attentional control, which were associated with decreases in functional activity in the inhibition network. Baseline functional activity in the inhibition network also predicted far-transfer to attentional control at post-test and follow-up. This provides a multi-level account of processes and individual differences underpinning successful transfer of cognitive training to real-world outcomes.

5.2. Introduction

Children and adults alike are faced with daily tasks that require careful direction of thoughts and actions. This is supported by cognitive control, a set of processes (e.g. working memory, cognitive flexibility and inhibition) critical for flexible goal-directed behaviour (Diamond, 2013). Childhood cognitive control has been shown to predict a range of social, academic, and mental health outcomes (Blair & Razza, 2007; Clark et al., 2010; Moffitt et al., 2011). In particular, better cognitive control has been associated with better personal finances, physical and mental health (Blair & Razza, 2007b; Clark et al., 2010; Moffitt et al., 2011). Impaired cognitive control has been linked to later mental health problems and criminality in adulthood (Moffitt et al., 2011). Cognitive control undergoes protracted development from childhood into early adulthood (Davidson et al., 2006; Garon et al., 2014; Wiebe & Karbach, 2017). supported by developmental changes in frontoparietal and frontostriatal neural circuitry (i.e. right inferior frontal gyrus, subthalamic nucleus, caudate, thalamus, putamen; Aron, 2007; Aron et al., 2007; Fiske & Holmboe, 2019). Given their critical role in healthy and productive development and coupled with prolonged plasticity of underlying neural circuitry, cognitive control functions have been primarily targeted (Diamond & Lee, 2011; Wass et al., 2012), and particularly so in childhood (Heckman, 2006).

Cognitive control interventions have focused on improving working memory, cognitive flexibility and to a lesser extent inhibition (Diamond & Ling, 2019; Kassai et al., 2019).There is broad consensus, that these cognitive control functions can be improved through training, albeit in a relatively narrow and often task-specific manner (i.e. near-transfer; Diamond & Ling, 2019; Holmes et al., 2019; Kable et al., 2017; Simons et al., 2016). Changes in other distally related domains of cognitive functioning and real-world outcomes (i.e. far-transfer) have been much less consistently observed (Holmes et al., 2019; Judd & Klingberg, 2021; Kable et al., 2017; Karbach & Verhaeghen, 2014; Kassai et al., 2019; Sala & Gobet, 2016, 2017; Scionti et al., 2020; Simons et al., 2016; Smithers et al., 2018). While opinions range in their optimism as to whether cognitive training can lead to far-transfer (Sala & Gobet, 2017, 2019), the quality of evidence has been consistently questioned (Shawn Green, 2020; Shawn Green et al., 2019). Given the likelihood of small effect sizes, criticisms have focused on small sample sizes, as well as training regimes lacking core features minimally required for far transfer (Diamond & Lee, 2011; Moreau & Conway, 2014; Raviv et al., 2022), such as variability, diversity and complexity of input. Further, training mechanisms appear to be poorly specified (Gobet & Sala, 2022; Shawn Green et al., 2019; Smid et al., 2020) with poor training designs.

Indeed, one potential reason for lack of far-transfer may be based on the unsuitability of current intervention designs for children, which in turn fail to maximise training gains. Cognitive control tasks are effortful and therefore, motivation could play a key role (Botvinick & Braver, 2015). For example, motivation may be an important factor of children's engagement with training tasks and determine the benefits they reap from the training tasks. In turn, this could determine the extent of transfer. One paper found that engagement was crucial to not only training gains, but also their maintenance (Johann & Karbach, 2020). One way to ensure high engagement and motivation is to use a gamified design. In addition to this, it may be crucial to ensure that the training is well-suited to children's abilities. Specifically, this may entail making training designs adaptive where they are scaled to children's baseline abilities but become more challenging as children get better at the tasks. Ensuring training is challenging enough will keep children motivated but scaling it within their abilities will ensure that children are still able to perform the tasks, minimising any feelings of frustration or discouragement which may lead to disengagement. Apart from maximising motivation, an adaptive design helps us reduce ceiling effects, where children can continue to reap benefits from the training intervention as they get better (Karbach et al., 2015). Indeed, previous training designs with an adaptive training protocol have been more successful in training cognitive control (Berkman et al., 2014; Verbruggen et al., 2013; Zhang et al., 2019; Zhao et al., 2015). These findings taken together suggest the need for training designs to be adaptive and gamified for both training groups to maximise training gains and extent of transfer.

Unlike for pharmacological treatments, active ingredients of psychological interventions are difficult to pinpoint (Sebastian et al., 2021). Based on correlations with outcome variables of interest, cognitive control interventions typically entail transforming experimental paradigms into training regimes (Spencer-Smith & Klingberg, 2017). For example, many cognitive control interventions entail working memory training, which usually consists of training memory span or n-back tasks and measuring performance-dependent increase or decrease of items (Judd & Klingberg, 2021; Klingberg, 2005), with the aim of improving academic achievement or fluid reasoning given high baseline correlations (Jaeggi et al., 2008). Computational modelling work has shown that mere covariance between training mechanism and outcome variable is not sufficient, however, to bring about change given that the relationship can be explained by other shared latent variables (Moreau & Conway, 2014). Thus, for working memory training increasing the number of items held in memory may not be the mechanism of interest, but rather a shared executive attention-control mechanism required for manipulating the information in a controlled fashion (Thorell et al., 2009; Thorndike & Woodworth, 1901; Unsworth & Engle, 2005), a task-feature that is rarely the intervention focus. In this study, we focus on training inhibition, and leverage response inhibition as the primary mechanism of action.

Compared to working memory, there has been much less focus on improving inhibition (Kassai et al., 2019). Based on a google scholar search conducted in September 2022, where the terms “working memory training” and “response inhibition training” were used, this search suggests that working memory training has been far more studied than inhibition (i.e. 9280 vs 307 studies). Existing studies predominantly focus on exploiting the bidirectional relationship between action (respond / inhibit) and valence (reward / punishment), by coupling specific specific stimuli with an associated action (Jones et al., 2016; Moreau & Conway, 2014; Noack et al., 2009). This has led for instance to healthier eating and drinking behavior after coupling stimuli of alcohol or fatty foods with inhibitory responses (Jones et al., 2016). Fewer studies train inhibition as a domain-general mechanism, measuring transfer independent of specific stimulus or action properties (though see here: (Berkman et al., 2014; Biggs et al., 2015; Delalande et al., 2020; Verbruggen et al., 2013; Zhang et al., 2019; Zhao et al., 2015). This is surprising given that inhibition involves a set of highly relevant and widely used processes including response inhibition or stopping, response selection and contextual monitoring (Chatham et al., 2012). As such, inhibition may offer a set of cognitive control processes that lend themselves ideally to training in terms of their domain general nature as well as the specifically identified training mechanism. Our state-of-the-art randomized control, leverages response inhibition as the core mechanism of action. Response inhibition has been shown to be core to numerous domains such as attention-deficit/hyperactivity disorder (ADHD), obsessive compulsive disorder (OCD) and academic performance (Blair & Razza, 2007; Mar et al., 2022; Wodka et al., 2007). Crucially, prior work has shown that these domains are affected by successful manipulations of response inhibition (Steinbeis, 2018; Verbruggen et al., 2012), going above correlational evidence to establish a central role of stopping in a range of cognitive processes. We were interested in whether inhibitory control training can lead to far transfer in a developmental sample. As an index of far transfer, we focus on real world attentional control, as measured by parent reports of ADHD symptoms. Response inhibition has been consistently reported to underlie attentional control, allowing for controlled allocation or orientation of attention to fulfil goals (Bari et al., 2020; Mackie et al., 2013; Wodka et al., 2007).

Understanding the nature of far transfer can be enriched by a more comprehensive assessment of processes underpinning training mechanisms and outcomes (Shawn Green et al., 2019). Specifically, the complex and multi-faceted nature of cognitive control calls for the integration of behavioural and neural indices. The neural circuitry underlying cognitive control and inhibition in particular is well documented and includes fronto-striatal regions such as right inferior frontal gyrus (IFG), right putamen, caudate, sub-thalamic nucleus (STN) and right thalamus (Aron, 2007; Aron et al., 2007; Buss & Spencer, 2014; Fiske & Holmboe, 2019). Known as ‘inhibition network’ these brain regions and their functional interaction undergo extensive development in early to mid-childhood (Buss et al., 2014; Buss & Spencer, 2014, 2018d).The malleability of cognitive control could therefore well be mediated by functional changes in this network. Changes in brain regions involved in inhibition have been observed following inhibition training in adults (Berkman et al., 2014), indicating a pattern that suggests a shift from reactive to proactive control modes (i.e. increasingly preparing to engage in cognitive control rather than responding to stop signals as and when they appear). How and whether such changes predict transfer and whether they do so in child development is unclear. Further, intervention gains are not homogeneous and vary between individuals (Könen & Karbach, 2015). Specifically, children with poorer cognitive control functions at baseline are reported to benefit the most from training (i.e. compensation effect; Karbach & Kray, 2009; Karbach & Unger, 2014; Traut, Guild, et al., 2021). This suggests that individual differences in a range of baseline indices of neural and cognitive functioning could be crucial to determining far-transfer to other domains. We used a combination of behavioural and neural indices to probe both the mechanisms underlying potential training-related change as well as offering a comprehensive assessment of individual differences likely to account for training success.

In sum, we trained inhibition (experimental group) and compared this to a training of response speed (control group) by using a well-powered, rigorous double-blind randomised controlled trial (RCT), leveraging a highly motivating gamified interface and maximal variation of training contexts and mechanisms. Crucially, we ensure optimal adaptiveness of the training protocol (Figure 5-1) by means of a trial-by-trial adaptation (using a staircase procedure) based on performance, ensuring that trials were scaled appropriately to individual's cognitive control abilities. We set out to test whether (i) cognitive control as operationalised through inhibition can be trained, (ii) whether this facilitates far-transfer to a real-world outcome (parent-reported attentional control), and (iii) how individual differences in changes and baseline abilities (in brain-behaviour) indices predict far-transfer. Our protocol and set of measures allows building a multi-level account of far-transfer. Children were randomly assigned to the Experimental Group (training inhibition; *N* = 119) or Control Group (training response speed; *N* = 116). Measures of training-related changes entailed near-transfer indices collected from the SSRT Task (i.e. SSRT scores and Go RT), far-transfer indices (i.e. parent-reported attentional control) as well as neural measures (i.e. task-related fMRI). Each of these was collected at three timepoints: pre-test (i.e. before training), post-test (i.e. after 8-week training) and at 1-year follow-up (note that neural data was not collected at 1-year follow-up; Supplementary Materials Figure 5-1). A high retention rate was achieved (71% participants retained from pre- to post-test; 99% participants retained from post-test to 1-year follow-up).

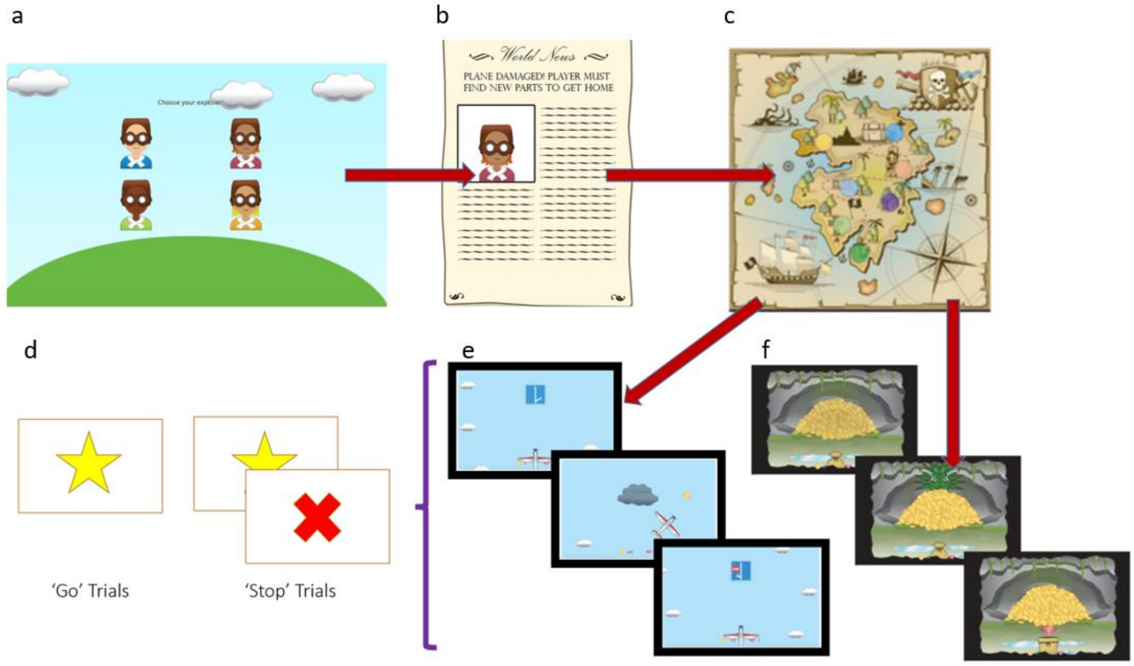


Figure 5-1. Training design where both groups were administered the same protocol, comprising a variety of adaptive and gamified tasks. (a-c), Children were told that they were a pilot who had crashed their plane on an island and had to navigate the island to earn coins. (d), Coins could be earned through games which operated on the same principle where they consisted of ‘go’ vs ‘stop’ trials. (e-f), Examples of these games have been provided.

5.3. Materials and Methods

5.3.1. Participants

A total of 262 typically developing children were recruited for the study (6.03-13.31 years; Age *M* = 8.97, Females = 52.84%) from schools within Greater London in the United Kingdom (data collection started in May 2019 and ended in May 2021). Parental consent was obtained beforehand and the study was approved by the UCL research ethics committee (Protocol number: 12271/001). There was no specific exclusion criteria, although for the scanning session a safety protocol was followed that excluded some children (e.g. metal in the body; claustrophobia). After exclusion of incomplete data, our sample consisted of 235 children. Socioeconomic status was assessed based on employment and education of both parents (Cirino et al., 2002; Hollingshead, 1975; von Stumm et al., 2020; Table S5-1). There was a positive skew in SES (*M* = 1.64; on a scale of 1-5 where 1 is the highest score attainable). Ethnic composition of our sample was as follows: Asian = 14.65%; Black = 3.18%; Mixed/multiple ethnic groups = 17.20%; White = 64.33%; Other = 0.63%. Children were randomly assigned to an experimental group training cognitive control (through inhibition) or to an active control group training response speed (Supplementary Materials Figure 5-1), with groups matched for gender and age.

5.3.2. Study Design

There were 4 main phases to the study. After an initial baseline data collection phase at pre-test, the 8-week computerised intervention was administered. This was followed up by a post-test and finally, a 1-year-follow-up. Behavioural, task-related fMRI tasks and parent reported attentional control (i.e. at pre-test, post-test, 1-year-follow-up) were collected to examine independent near- and far-transfer changes.

Due to disruptions to in-person testing during the Covid-19 pandemic, no MRI was obtained at 1-year follow-up (Supplementary Materials Figure S-15). Retention was 71.24% from pre- to post-test and 99.40% from post-test to 1-year follow-up; Supplementary Materials Figure S-15).

5.3.3. Training Games

Training was presented in the form of a computerised web-based Treasure Game. The training was designed to last 8 weeks, with four recommended sessions per week, one taking place at school and three at home. Each session was programmed to take approximately 15 minutes.

Both groups received identical training in terms of narrative, stimuli and intensity (Figure 5-1). The only difference between the groups was how participants were instructed to respond to the stop stimuli (i.e. inhibit for the experimental group and respond for the control group; further details in Supplementary Materials-5). Once every week, information regarding children’s motivation was collected (Supplementary Materials-5).

5.3.3.1. Experimental Group: Inhibition training

To train inhibition a stop signal response task was used. Participants were instructed to press the spacebar on presentation of a ‘go’ signal. On stop trials where a ‘stop’ signal appeared after the ‘go’ signal, participants were instructed to inhibit pressing the spacebar (however see Supplementary Materials for specific descriptions of each training game and training mechanism). ‘Go’ and ‘stop’ signal stimuli and inhibition mechanism varied according to the game being played. The stop signal delay (SSD) was initially set at 200ms. After successful inhibition, the

SSD would decrease by 50ms and after failed inhibition, it would increase by 50ms (Logan, 1997; Verbruggen & Logan, 2009). This ensured that the training was adaptive. Stop trials occurred 26-47% for each training session. To ensure adaptiveness across training sessions, the SSD of each subsequent session was taken from the final ‘stop’ trial of the preceding session on that specific training game.

5.3.3.2. Control Group: Response speed training

The response speed training was identical to the experimental condition in all aspects except that a response was required for all signals. Participants were instructed to press the spacebar as quickly as possible. To ensure that training was adaptive for this group, participants had to respond within a time window that was set based on a rolling average of the response time of the previous ten trials plus two standard deviations. This ensured that the training was adaptive, while minimising the effect of outliers on the response threshold.

5.3.4. Pre-post tasks

Numbers available for each task have been outlined in Table S5-2.

5.3.4.1. Stop-signal reaction time task

A measure of cognitive control was administered at each testing time-point before and after training via a child-friendly version of the SSRT (Matzke et al., 2018) (Supplementary Materials Figure S1). Ten practice trials were administered before 80 trials of the main task. Each trial started with the presentation of a fixation cross of 1250ms. During the task, participants were asked to press the left arrow key when seeing the go signal (i.e. a honey pot) on the left side of the screen and the down arrow key when the signal appeared on the right side. On 25% of the trials (i.e. ‘stop’ trial) a picture of bees was presented after the honey pot. This served as the ‘stop’ signal. The stop signal delay (SSD) started at 200ms and decreased by 50ms after a successful ‘stop’ trial and increased by 50ms after an unsuccessful ‘stop’ trial. Several studies have validated the SSRT as a measure of response inhibition (Logan et al., 2014) and it is correlated with self-report measures of impulsive behaviours in young adults (Logan, 1997). The task was presented using the software Presentation (www.neurobs.com; Version 23). However, it was administered online via Gorilla during remote testing (www.gorilla.sc; A. Anwyl-Irvine et al., 2021; A. L. Anwyl-Irvine et al., 2020).

5.3.4.2. Task-related functional Magnetic Resonance Imaging (fMRI).

The same SSRT task used outside of the scanner was employed. Data was acquired with a standard whole-head coil on a 3.0 Tesla Siemens Prisma Scanner at the Birkbeck-UCL Centre for Neuroimaging. Two event-related runs of the SSRT task (i.e. 54 trials per run) were administered, lasting approximately 5 minutes each, and were acquired using T2*-weighted echo-planar imaging (EPI; TR = 1.25s, TE = 35.2 ms, sequential acquisition, 60 slices of 2 x 2 x 2 mm^3 voxels, field of view 1696 x 1696, 106 × 106 matrix, in-plane resolution 2 mm). After the functional runs, to obtain a scan for anatomical reference, magnetisation-prepared rapid gradient-echo sequence (MP-Rage) was used (TR = 2.30s TE = 2.98ms, flip angle = 8°, slices = 1 x 1 x 1 mm^3 voxels, field of view 256 x 256). To reduce head motion, children were told to keep their head as still as possible and foam inserts were placed between the head and the head coil. Visual stimuli were projected onto a screen in the magnet bore that could be viewed through a mirror attached to the head coil. The task was presented using the software Presentation (www.neurobs.com; Version 23).

5.3.4.3. Real-world attentional control outcome

We used the attention deficit hyperactivity disorder scale (ADHD) from the Child and Adolescent Symptom inventory-4R (CASI-4R) as a proxy of a real-world measure of attentional control (Gadow, 2005). Previous studies examining clinical and non-clinical samples have found that the CASI-4R has good test-re-test reliability, validity and internal consistency (Salcedo et al., 2018). Subscales of inattention and hyperactivity-impulsivity were administered consisting of a total of 18 items. This was administered to the parents of participants where they answered questions about their child's behaviour on a 5-point scale ('Never' to 'Very often'). Example of items included 'Has difficulties paying attention to tasks and activities', 'Has difficulties controlling worries' and 'Acts restless and edgy'.

5.3.5. Statistical Analysis

5.3.5.1. SSRT

Reaction times below 100ms and above 5000ms were excluded based on previous literature (Luce, 1986). To derive a measure of inhibition, mean SSRT scores were calculated using the integration method (Verbruggen et al., 2013, 2019). Reaction times on correct 'go' trials (i.e. mean Go RT) were also computed to examine slowing of responses.

5.3.5.2. FMRI

Each individual's functional scans were realigned to correct for head motion by initial realignment to first image and second realignment to mean image). The realigned scans were co-registered with anatomical T1-weighted images and spatially normalized to the standard Montreal Neurological Institute (MNI) space by resampling to a voxel size of 2 × 2 × 2 mm^3. Normalized images were smoothed with an 8-mm Gaussian filter. Fixed statistical effects were calculated at the individual level by modelling each trial condition (‘stop’ successful, ‘stop’ unsuccessful, ‘go’ successful and ‘go’ unsuccessful) with a stick function convolved with the canonical hemodynamic response function. To reduce movement-related artefacts, six motion parameters were included as regressors, as well as an additional regressor to model images that were corrupted due to head motion >1.5 mm and were replaced by interpolations of adjacent images (<10% of participant's data). To examine training-related changes from pre- to post-test in stop vs go trial condition, the Sandwich Estimator Toolbox for Longitudinal and Repeated Measures Data v2.1.0 was employed (SwE, toolbox for SPM, Guillaume et al., 2014). Repeated measures ANOVA was conducted at the group level, with the stop successful condition and go successful condition entered as fixed effects, and a subject factor entered as random effects. Family wise error-corrections (FWE) at P <.05 (cluster-level extend threshold) were applied to the data based on an uncorrected height threshold of p < .001. Moreover, using the MarsBaR Toolbox (Brett et al., 2002) implemented in SPM12, we extracted functional activity from the inhibition network (i.e. specifically on contrasts comparing successful ‘stop’ trials vs successful ‘go’ trials). Based on previous literature, this included the right caudate (center of mass = 15, 11, 8), right putamen (center of mass = 28, 4, 1) and right thalamus (center of mass = 13, −19, 7), comprised of anatomical AAL ROIs selected from the MarsBaR-AAL ROIs (Thompson et al., 2021). Additionally, the right IFG pars triangularis was selected from the probabilistic Harvard-Oxford atlas (thresholded at 20%, center of mass: 51, 28, 8) and the right subthalamic nucleus (STN) was selected (Forstmann et al., 2010; Thompson et al., 2021; center of mass: 9, −13, −7). Beta values for each ROI (i.e. successful 'stop' trials vs successful 'go' trials) were extracted for further statistical analyses outside of SPM.

5.3.5.3. Real-world attentional control

For each individual, scores for hyperactivity and inattention scales were summed as we did not have specific hypotheses about each individual construct. A higher score indicated worse attentional control.

5.3.5.4. Training effects on pre-post measures.

Main effects of training group and session were examined using a mixed model. To examine training-related differences pre-test and post-test were entered as sessions. To examine long-term training-related differences pre-test and 1-year follow-up were entered as sessions. Significant interaction effects between Session and Group were interpreted as training-related changes and followed up with post-hoc paired t-tests. FDR adjustments were applied to p-values from the mixed models (i.e. Benjamini-Hochberg Procedure). Bonferroni corrections were applied to all post-hoc t-tests.

5.3.5.5. Predictors of Far Transfer

Regression models were used to examine predictors of far-transfer in attentional control. To examine how independent baseline indices predicted changes in attentional control, SSRT, Go RT and functional activity in the inhibition network (i.e. successful 'stop' trials vs successful 'go' trials) were entered into a multiple regression model. In a second model, we examined how changes in our independent behavioural (i.e. SSRT and Go RT) and neural (i.e. functional activity in the inhibition network) indices predicted changes in attentional control. This allowed us to probe at potential processes that may facilitate far-transfer. Age and training slope were added in as covariates for all models. To examine if groups varied on coefficients, model comparisons were run with F-statistic and degrees of freedom reported. Specifically, a model where slopes were constrained to be equal was compared to one where slopes were allowed to vary. A significant difference between the models indicated group differences. All p-values of interest were adjusted using a FDR correction (i.e. Benjamini-Hochberg procedure). Using these methods, we examined both predictors of immediate far-transfer (i.e. comparison of pre-test and post-test) and long-term far-transfer (i.e. comparison of pre-test and 1-year follow-up). Findings were cross-checked with LCS models (Supplementary Materials-5).

5.3.5.6. Data imputation.

Multiple Imputations by Chained equations (MICE) was used to impute missing data (predictive mean matching; iterations = 20, *N* datasets = 100). Distributions of actual and imputed datasets were checked to ensure reliability of imputation (Supplementary Materials Figure S-16). A single imputed dataset was used as this was necessary in conducting mixed models with post-hoc tests and LCS modelling. We ensured the replicability of these results by re-running the process multiple times and choosing a dataset at random.

5.4. Results

5.4.1. Baseline correlations at pre-test

Cross-sectional correlations at pre-test revealed significant correlations between SSRT scores and Go RT scores (*r* = -.20, *p* = .009) as well as between functional activity in the inhibition network and attentional control scores (*r* = .18, *p* <.001). All other correlations were not significant (*p* > .125; Table S5-3).

5.4.2. Training Indices

Training took place over an 8-week period. The groups did not differ in training intensity or motivation and showed improvements during training in the targeted processes (Figure 5-2). Exact statistics on training indices have been provided in Chapter 4 (Section 4.4.1).

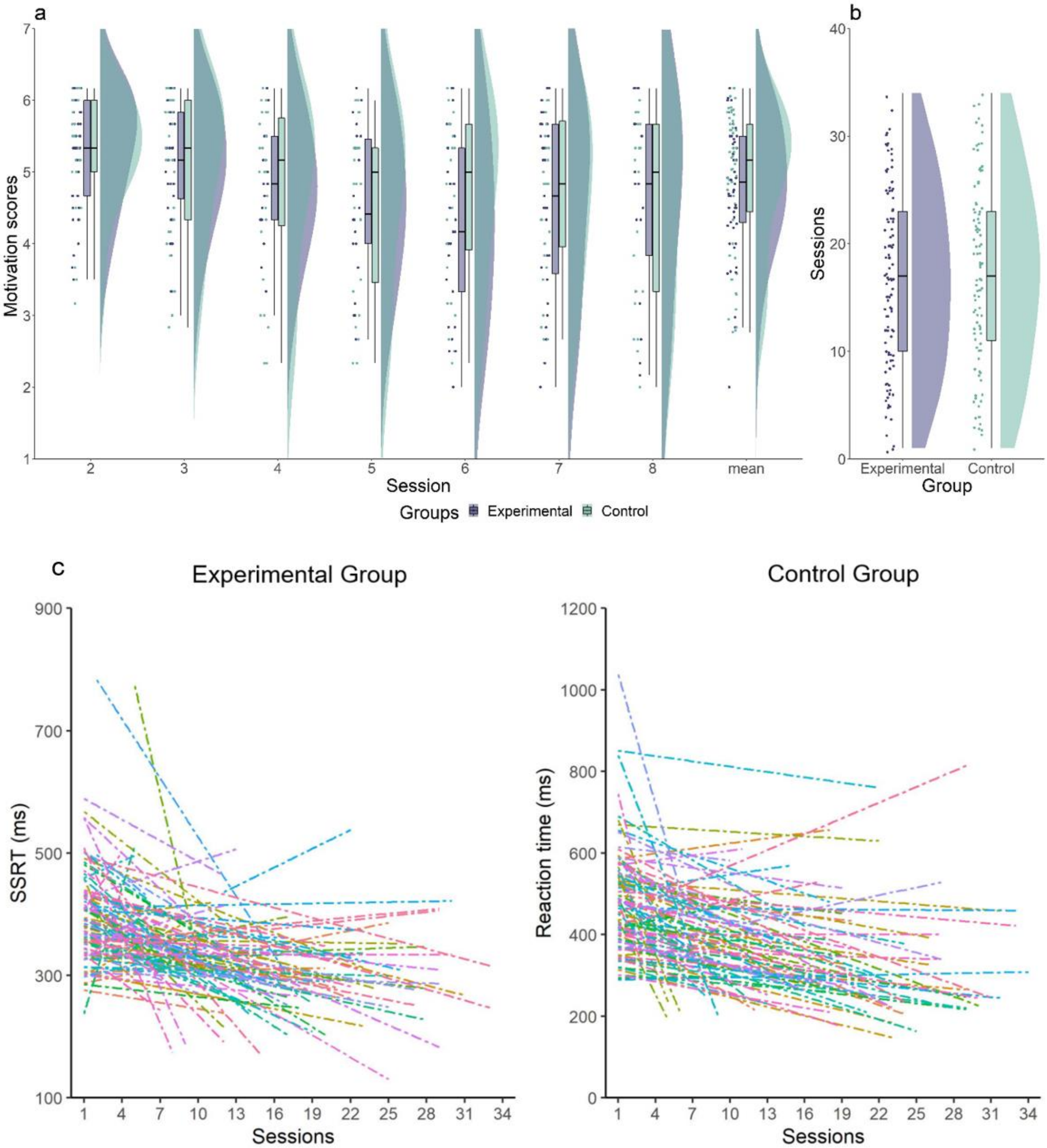


Figure 5-2. Training-related indices. (a), Motivation in both groups was comparable. (b), Comparable number of sessions performed by both groups. (c), Lines reflect individuals in the Experimental and Control group where improvements in respective domains as a function of training were observed. Both groups improved in their respective domains as a function of training.

5.4.3. Immediate training-related changes

5.4.3.1. Near-transfer

A mixed model revealed a significant interaction between Session and Group in SSRT scores (*F* (1,221.98) = 13.19, *p* = .001) with this interaction remaining after age was controlled for (*F* (1,219.89) = 12.26, *p* = .002). Follow-up paired t-tests comparing pre-post training scores revealed that SSRT scores improved significantly in the experimental group (*t* (225) = -4.51, *p* <.001, *d* = .44; Figure 5-3a). No differences in SSRT scores were observed in the control group (*t* (226) = 0.65, *p* > .999, *d* = -.09; Figure 5-3a).

We also looked at responses to 'go' stimuli. These are of interest in terms of indexing changes for the response speed group, as well as providing a measure of proactive slowing (Martoni et al., 2018) for the experimental group. A significant interaction between Session and Group in Go RT was observed (*F* (1, 222.99) = 35.06, *p* = .001). This interaction was still significant after controlling for age (*F* (1,222.57) = 36.32, *p* <.001). Follow-up paired t-tests comparing pre-post training scores revealed that reaction times increased in the experimental group (*t* (226) = 4.07, *p* <.001, *d* = -.41*;* Figure 5-3b and decreased in the control group (*t* (225) = -4.297, *p* <.001, *d = .40;* Figure 5-3b).

5.4.3.2. Far-Transfer

A mixed model revealed a significant interaction between Session and Group in attentional control (*F* (1 218.61) = 5.88, *p* = .032) with this interaction remaining after age was controlled for (*F* (1,217.71) = 5.82, *p* = .034). Follow-up paired t-tests comparing pre-post training scores revealed that attentional control improved significantly in the experimental group (*t* (218) = 3.19, *p* = .010, *d* = .27; Figure 5-4).

No changes in attentional control were observed in the control group (*t* (217) = -0.25, *p* > .999, *d* = .07).

5.4.3.3. Functional activity in the inhibition network.

Functional imaging data was analysed at the whole-brain level and looking at regions of interest (ROIs) comprising the inhibition network. Whole-brain analysis at pre-test revealed significant activity (FWE-corrected at cluster-level, based on an uncorrected height threshold of *p* < .001) in the right insula (MNI coordinates = -36, 22, 4; number of voxels = 784; Z = 3.14, *p* = .014), left insula (MNI coordinates = -32, 24, 0; number of voxels = 356; Z = 2.92, *p* = .025), right frontal eye fields (MNI coordinates = 6, 20, 44; number of voxels = 379; Z = 2.88, *p* = .028; Figure 5-5a). There was no interaction between Session and Group found (i.e. no-significant changes in any brain regions follow-training specific to either group). For the ROI analysis, contrast estimates for each participant were extracted from a set of brain regions typically involved in inhibition and averaged (Figure 5-5b). Mixed model analysis revealed a main effect of time in functional activity in the inhibition network (*F* (1,193.94) = 18.86, *p* <.001), showing a significant reduction in functional activity from pre- to post-training *(t* (203) = 4.86, *p* <.001, *d* = -.34*;* Figure 5-5c). No interaction between Session and Group was found (*F* (1,193.94) = 0.66, *p* =.417).

5.4.4. Predictors of immediate far transfer

We examined predictors of far-transfer using multiple regression analyses (with age and training slope entered as covariates. We began by running a model using baseline attentional control scores to predict training-related changes in attentional control in both groups. In both groups, changes in attentional control were strongly predicted by pre-test attentional control scores (Experimental Group: β [95%

CI] = -0.70 [-0.76, -0.64], *p* <.001 and Control Group: β [95% CI] = -0.66771 [-0.76, -0.58], *p* <.001; Figure 5-6a). This suggests regression to the mean rather than any meaningful compensation effect as it was found in both groups (Castro-Schilo & Grimm, 2018; Eriksson & Häggström, 2014; Glymour et al., 2005; Könen & Karbach, 2015; Sorjonen et al., 2019). Then, we examined how baseline individual differences in independent behavioural (i.e. SSRT, Go RT) and neural (i.e. functional activity in the inhibition network) indices predict changes in attentional control. Second, we examined how changes in our independent behavioural and neural indices may predict attentional control changes. To examine group differences, a model where slopes for both groups were equal for both groups was compared to a model where slopes were allowed to vary. Findings were cross-checked for reliability using Latent Change Score Models (see Supplementary materials). We note two key findings. First, improvements in attentional control were predicted positively by pre-test functional activity in the inhibition network but only in the experimental group (*β [95% CI]* = -0.69 [-0.88, -0.50], *p* = .002; group differences: (*F* (2,203) = 4.72, *p* = .020; Figure 5-6b). Secondly, training-related decreases in functional activity in the inhibition network predicted a training-related increase in attentional control, and did so only in the experimental group (β [95% CI] = 0.35 [0.21, 0.49]***,*** *p = .041*; group differences: *F* (2,203) = 3.03, *p* = .0504; Figure 5-6c).

5.4.5. Long-term training-related changes

5.4.5.1. Near-transfer

A mixed model revealed a significant interaction between Session and Group in SSRT scores (*F* (1, 233.49) = 4.15, *p* = .043, although does not survive FDR correction: *P* = .085). Follow-up paired t-tests indicated that these improvements were sustained at a 1-year follow-up as indicated by direct comparison of pre-test and 1-year follow-up (*t* (225) = 4.90, *p* <.001, *d* = .51; Figure 5-3a). Follow-up paired t-tests in the control group revealed no significant differences between pre-test and 1-year follow-up (*t* (223) = 0.65, *p* = .278, d = .19; Figure 5-3a).

We also looked at responses to ‘go’ stimuli. A significant interaction between Session and Group in Go RT was observed (*F* (2, 444.59) = 8.39, *p* = .016). This interaction was still significant after controlling for age (*F* (2,440.01) = 8.67, *p* = .011). Follow-up paired t-tests revealed that increases in reaction times were sustained at 1-year follow-up (*t* (228) = 5.97, *p* <.001, *d* = -.57*;* Figure 5-3b). In the control group, change was not sustained at 1-year follow up (*t* (225) =1.98, *p* = .297, *d = -.17;* Figure 5-3b).

5.4.5.2. Far-Transfer

A mixed model revealed a non-significant interaction between Session and Group in real world attentional control (*F* (1, 222.03) = 0.47, *p* = .494; Figure 5-4).

5.4.6. Predictors of long-term far-transfer

Similarly, to test for the contribution of individual differences to far-transfer at 1-year follow-up multiple regression analysis with the application of FDR correction (cross-checked for reliability using Latent Change Score Models; see Supplementary materials). Age and training slope were controlled for. Similarly to immediate far-transfer, we observe regression to the mean in baseline attentional control scores where changes in attentional control were predicted by pre-test attentional control scores for both experimental (*β [95% CI]* = -0.35 [-0.43, -0.27], *p* <.001) and control groups (*β [95% CI]* = -0.60 [-0.69, -0.52], *p* <.001; Figure 5-6d) (Castro-Schilo & Grimm, 2018; Eriksson & Häggström, 2014; Glymour et al., 2005; Könen & Karbach, 2015; Sorjonen et al., 2019). Then, we examined how baseline individual differences in independent behavioural (i.e. SSRT, Go RT) and neural (i.e. functional activity in the inhibition network) indices predict changes in attentional control. Second, we examined how changes in our independent behavioural indices may predict attentional control changes, hinting at a process that may underlie far-transfer. To examine group differences, a model where slopes for both groups were equal for both groups was compared to a model where slopes were allowed to vary. We note a key finding. In the experimental group, improvements in attentional control were predicted by greater pre-test functional activity in the inhibition network (*β [95% CI]* = -0.63 [-0.81, -0.45], *p* = .002; lack of group differences: *F* (2,204) = 1.74, *p*= .179; Figure 5-6e).

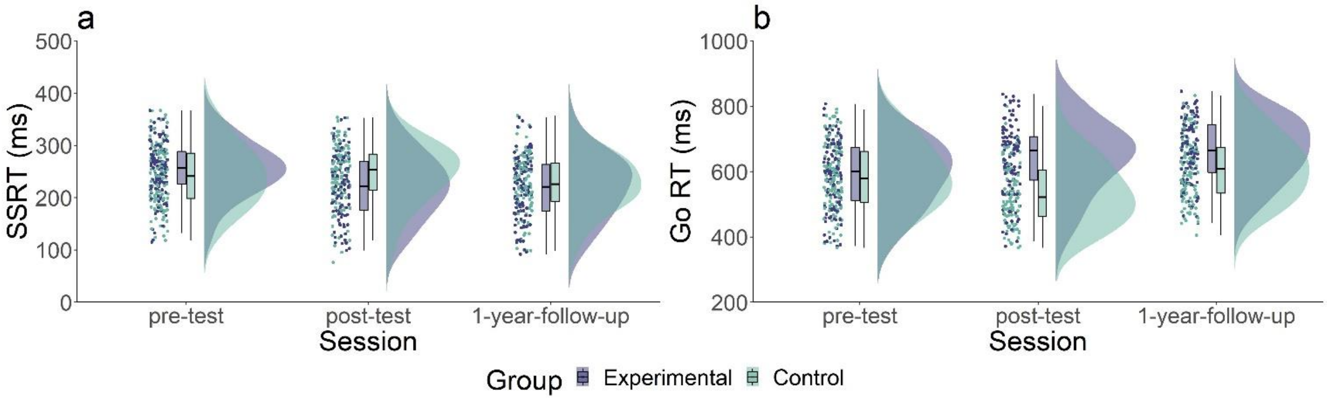


Figure 5-3. Training- and session-related changes in SSRT Task**.** (a), training related improvements in inhibitory control observed for experimental group from pre- to post-training, which are maintained at 1-year follow-up. (b), training-related slowing of responses for experimental group from pre- to post-training, which are maintained at 1-year follow-up.

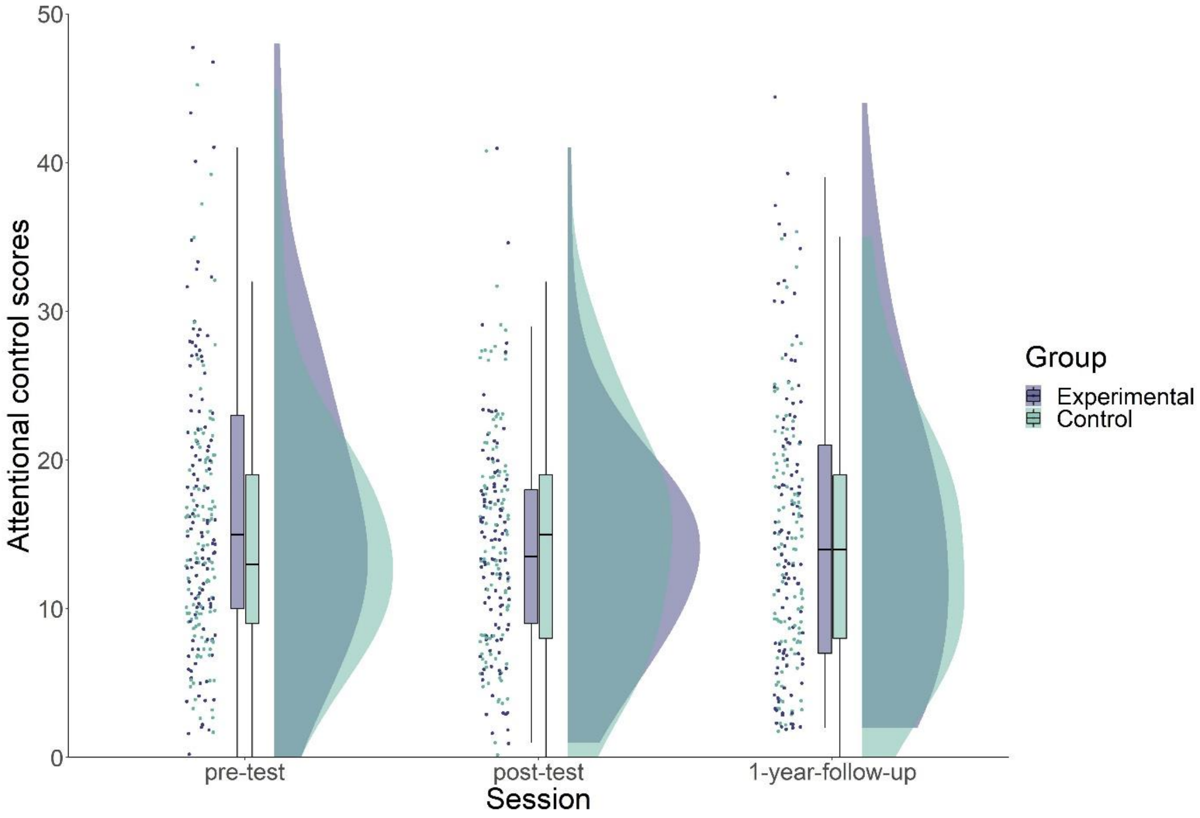


Figure 5-4. Attentional control. Immediate Training-related improvements in attentional control were observed after training. However, long-term training-related improvements were not observed. *Note: Attentional control scores are indicated by attentional problems where a reduction in scores indicates improvements.*

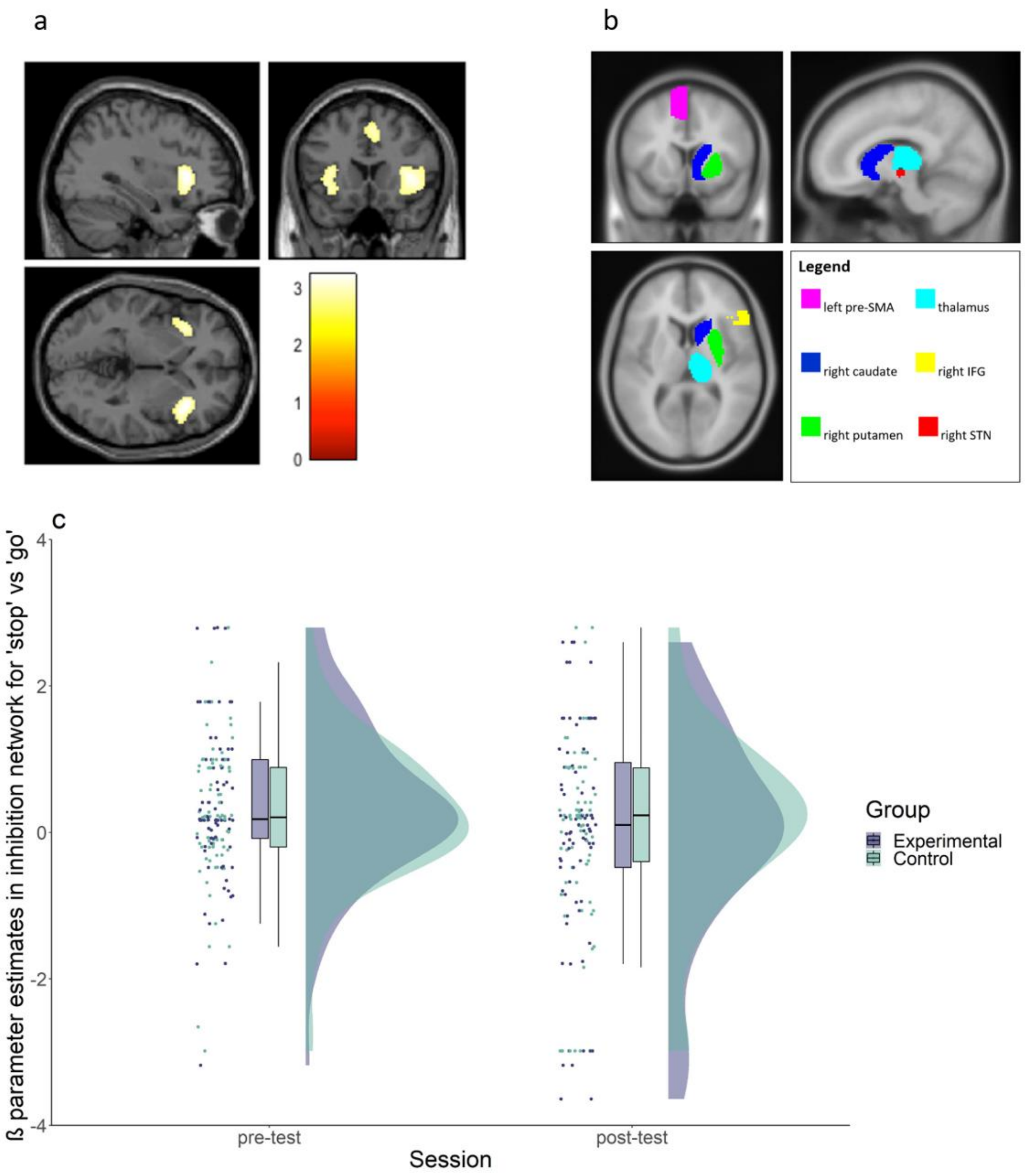


Figure 5-5. (a), Significant bilateral activation in the insula and right FEF at pre-test shown with FWE correction applied at cluster-level, based on an uncorrected height threshold of *p* < .001. (b), Areas included in the inhibition network and (c), No training-related changes were observed in functional activity in the inhibition network.

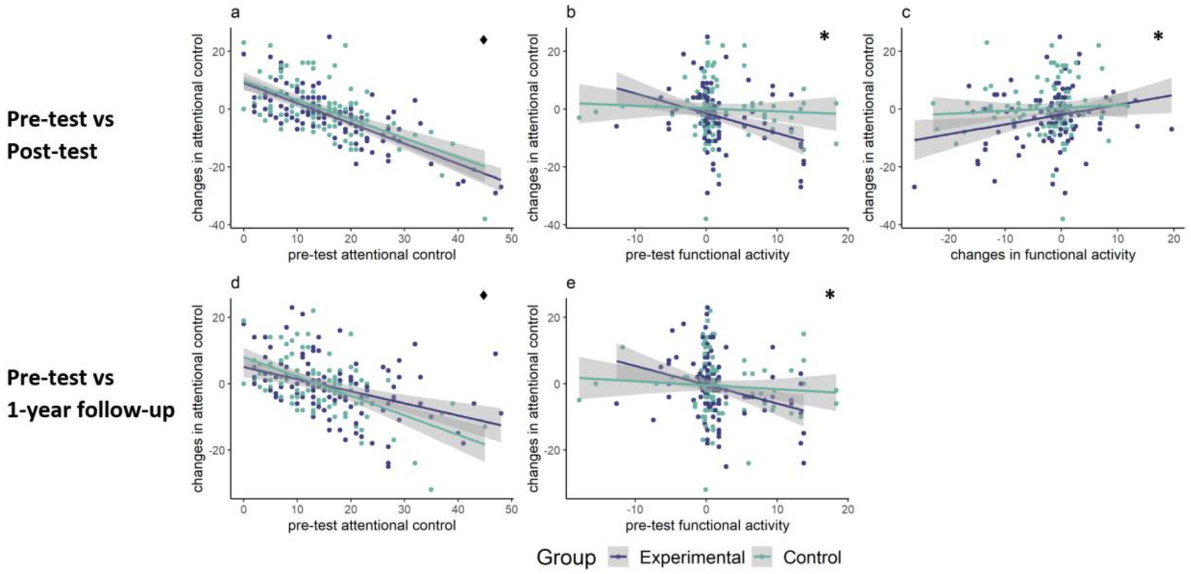


Figure 5-6. Individual differences that predict far-transfer to attentional control. (a-c), Training-related improvements in attentional control at pre-post test was predicted by baseline and changes in functional activity in the inhibition network. (d-e), Training-related improvements in attentional control at 1-year follow-up was predicted by baseline functional activity in the inhibition network. *Note: Diamond indicates significant for both groups at p <.050. Asterix indicates significant only for experimental group at p <.050. Attentional control scores are indicated by attentional problems where a reduction in scores indicates improvements.*

5.5. Discussion

Our study used a large-scale RCT to test whether compared to a response speed training, cognitive control training leads to changes on real world outcomes of attentional control. We demonstrate a high degree of similarity and comparability between both groups in amount of training and motivation to train and further show that during training both groups improved on the cognitive functions targeted by the intervention, demonstrating that training was successful. In terms of changes following training, we show that changes in response speed and inhibition were specific to each training group reflecting improvements in the trained processes. In the case of Go RTs, a marker of proactive control these were sustained at 1-year follow-up. Crucially, only the experimental group demonstrated improvements in proxies of real-world (parent-reported) attentional control. Whereas no clear neural mechanism could be identified, training-related changes in functional activity of the inhibition network predicted improvements in attentional control as measured by ADHD symptoms. Finally, individual differences in the inhibition network at baseline predicted training-related improvements in real-world attentional control at both post-test and follow-up. Using a highly powered and optimised intervention design this study demonstrates that cognitive control in middle childhood can be improved, translating onto real-world domains, which can be predicted by functional activity in the underlying neural architecture.

Previous work suggests the importance of diverse, complex, variable and challenging environments (Diamond & Lee, 2011; Raviv et al., 2022; Smid et al., 2020) to ensure a high degree of sustained motivation as well as learning and generalisation. We adopted a gamified approach and implemented a variety of features to ensure that training for both groups was adaptive and therefore challenging, varying training contexts, stimuli and mechanisms throughout the training period. As a result, motivation was consistently high, as indicated by the overall retention in our sample was high (71-99% from pre-post-test and the 1-year follow-up, with the drop from pre- to post-test presumably partly reflecting the impact of Covid-19) and the high motivation ratings over the 8 weeks of training. Both groups performed an equal number of sessions and showed comparable improvements on their targeted cognitive functions as indicated by changes during the training sessions. Our intervention design therefore ensured optimal conditions for learning and generalisation and more importantly, highly comparable engagement and improvement in targeted functions for both training groups. This is an ideal starting point from which to interpret any group differences in training outcomes.

While the control group showed short-lived changes in response speed from pre- to post-test, only the experimental group improved in inhibition, as indicated by both response times to ‘stop’ and ‘go’ signals. Both were sustained at 1-year follow-up (although the measure of SSRT does not survive FDR correction and requires caution), suggesting that our cognitive control training is promising in producing lasting changes (Boehler et al., 2012). These findings add to a substantial body of literature on near transfer effects in cognitive training (Sala & Gobet, 2016, 2017; Smithers et al., 2018). Maintenance of training effects have been inconsistent in the literature (Ball et al., 2002; Klingberg et al., 2005) although motivation has been found to be key to long-term training improvements (Johann & Karbach, 2020). Our variable and engaging protocol could have been key to sustained improvements in our sample. We show particularly strong sustained changes in reaction times in response to ‘go’ stimuli in the experimental group suggests that the training led to strategic slowing and thus altered proactive control processes (Martoni et al., 2018). In line with our prediction, our cognitive control training targeting inhibition led to a host of improvements not just related to motoric stopping, but also contextual monitoring.

Crucially, this study was able to show training-related improvements in real world attentional control following cognitive control training. Our proxy for this were parent reports on everyday inattention and hyperactivity, a measure that captures a range of different situations and everyday contexts and has high validity and reliability (“5th World Congress on ADHD, 2015; Brown et al., 2010; Salcedo et al., 2018). We therefore provide evidence that lab-based interventions of cognitive control can lead to changes beyond the lab and to real world outcomes. Given the crucial role of attentional control in academic settings(Rueda et al., 2010), social situations (Normand et al., 2014) and more generally for well-being and mental health (Derakshan & Eysenck, 2009; Rueda et al., 2010), this finding has crucial policy ramifications. These findings also identify a potential causal link between cognitive control and later life outcomes, namely attentional control, which further studies may wish to explore and target more explicitly (Wass et al., 2011, 2012).

At pre-test, children were found to recruit areas in the inhibition network while performing our SSRT inhibition task (Cai et al., 2014). Contrary to a previous study in adults (Berkman et al., 2014), activity in this network was not modulated as a function of training. Instead, we found a decrease from pre- to post-training for both training groups. We offer three interpretations for this null finding: first, owing to Covid restrictions fewer children participated in the MRI following training and as such we may have been underpowered to detect reliable group differences following training. Second, it is likely that training might have intensified pre-existing differences in task strategies (i.e. reactive and proactive control), which in turn could have led to a greater heterogeneity of task-related neural activation. This interpretation is buttressed by prior work showing that training-related changes in inhibition are best explained by qualitative shifts in neural networks as opposed to homogeneous quantitative changes in the same network (Berkman et al., 2014). Finally, functional MRI is susceptible to noise (Bennett et al., 2009) and therefore, reliable group-related differences may not have been observed. It could be possible that MRI data is noisier in children. To minimise this, we note that proper denoising protocols were applied to our developmental data (Fassbender et al., 2017). Despite this, it is possible that children may have had a harder time maintaining attention in the scanner in comparison to adults which could have impacted the observation of training-related neural changes. We note that one previous developmental study found training-related structural changes in inhibition-related areas, however this finding should be approached with caution as reported effects were small with non-application of multiple corrections (Delalande et al., 2020).

While we could not identify a clear functional neural mechanism underpinning the observed training-related changes in cognitive control, we found that changes in functional activity in the inhibition network predicted changes in attentional control in the experimental group. Specifically, a decrease in activity accounted for an increase in attentional control following training. Interestingly, while both groups show an overall decrease in functional activation, only in the experimental group does this change predict improvements in attentional control, suggesting a specific involvement of the inhibition network in accounting for training-related improvements in attentional control. The direction of this relationship is compatible with the hypothesis that cognitive training alters neural efficiency of cognitive control processes (Adibi et al., 2013; Bonnasse-Gahot & Nadal, 2008). While it has been argued and reported elsewhere that trained neural processes require less neural energy (Giehl et al., 2020; Neubauer & Fink, 2009), the exact direction of the relationship between activation and performance remains difficult to interpret in the absence of indices of performance strategy (Poldrack, 2015). We also show that baseline differences in functional activity in the inhibition network predict changes in attentional control both at post-test as well as follow-up for the experimental group only. These effects are striking in that they are highly specific only to baseline functional activity (and no other baseline indices) in the experimental group. Process-relevant functional activity has been shown to predict treatment outcomes across a range of clinical and training-related settings (Baykara et al., 2020; Crane et al., 2017; Heinzel et al., 2014; Månsson et al., 2022; Pagliaccio et al., 2019). This has practical relevance given the considerable time, effort, and opportunity costs of engaging in cognitive training.

We note that there was no significant difference in attentional control between pre-test and the 1-year follow-up. Presumably, there are considerable individual differences in the maintenance of the training effects and indeed the relationship with baseline functional activity seems to speak to this. Despite our non-clinical population, our findings related to attentional control (measured through ADHD symptoms) hold clinical relevance. ADHD is commonly associated with negative outcomes such as poor academic performance (Polderman et al., 2010), elevated rates of antisocial behaviour (Thapar et al., 2006) and substance abuse (Groenman et al., 2017). Our study shows promise in improving ADHD symptoms, which in turn may help elevate later poorer outcomes associated with it.

Is cognitive control trainable and is far transfer possible? Our findings suggest that it depends. Effectiveness of cognitive control interventions depend on the features of the training design itself (i.e. gamified, adaptive features determining motivation). However, they also rely heavily on the individuals themselves with huge intra-individual variability observed. While one possible solution to this is to create personalised training regimes (Smid et al., 2020), the plausibility of this given limited resources needs to be re-evaluated. Additionally, we recognise our study is limited in investigating the malleability of cognitive control as it focused on a singular measure of real-life outcome. Therefore, it is unclear if transfer to other domains such as mental health/emotional wellbeing can be produced. This highlights the complex and heterogenous nature of training cognitive control. It further suggests that a different approach needs to be taken to ensure maintenance of transfer into a diverse range of real-life measures.

In conclusion, our gold-standard training protocol allowed us to reliably investigate near- and far-transfer effects of cognitive control training. Training-related near-transfer was observed in response inhibition and proactive control as well as in far-transfer (i.e. parent-reported attentional control). These improvements were linked to training-related decreases in functional activity in the inhibition network. Further, individual differences in neural substrates were a crucial predictor of attentional control improvements as well as their maintenance. Our multi-level account on far-transfer has implications for future intervention designs as well as clinical implications for populations with ADHD.

5.6. Supplementary Materials

5.6.1. Training Protocol

Participants were introduced to the training games as the ‘Treasure Game’ with the narrative that they had flown a plane, which had to crash land in the desert. In order to fix their plane, they were required to obtain spare parts from a sage, living in a distant cave. To get to the sage, participants had to travel through 4 different worlds (i.e. forest, desert, snow and mountains), after which they had to go back through the same worlds to return to the plane. While travelling through each world, participants could collect coins and gems, which could be used to trade for spare parts with the sage. Gems and coins were collected in the context of seven different games that were designed to train inhibition (experimental group) and response speed (control group). The seven training games were 1) Treasure collect, 2) Mining, 3) Chest picking, 4) Conveyor belt, 5) AB Driving, 6) Hold-and-Release (HR) Driving and 7) Forest Escape (refer to Chapter 2 for more details on responses). Each training session entailed a combination of two games, which was set in a pre-assigned order at the start of training. Before starting the games, participants were presented with an option of three different caves that they could choose from to encourage engagement and a sense of agency.

Session recoding and inclusion. For both groups, sessions were recoded based on date, meaning any data logged on the same date would be grouped in the same session. Since the implementation of the games differed in terms of key presses and mechanisms tested (Figure 5-1), we only included sessions for participants that had a minimum of 2 games and, for the experimental group only, sessions that had at least two games with valid SSRT measures (i.e. positive SSRT values). For the control group, reaction times were included that were within 2 standard deviations of the mean reaction time per participant.

5.6.2. Motivation Questionnaire

*T*he questionnaire consisted of 6 items: “1. I like the training; 2. I like to do the training; 3. I do not always feel like training; 4. I think I can become better through the training; 5. I find the training boring; 6. I am getting better at the training tasks”. Items 3 and 5 were reverse coded.

5.6.3. LCS Model Fits

Models were estimated in the lavaan package for R (Version 5.23) using full information maximum likelihood, robust (Huber-White) standard errors and a scaled test statistic. Overall model fit was assessed using root-mean-square error of approximation (RMSEA; acceptable fit: < 0.08; good fit: < 0.05), the comparative fit index (CFI; acceptable fit: 0.95 to 0.97; good fit: > 0.97) and the standardized root-mean-square residual (SRMR; acceptable fit: 0.05 to 0.10, good fit: < 0.05). We fit a quad-variate model examining changes in our measures between pre-test and post-test. Before fitting a quad-variate model, we fitted a univariate to our four measures (i.e. SSRT, Go RT, functional activity, attentional control). Our measure of SSRT and Go RT showed a poor model fit (RMSEA = 0.140, 90% confidence interval (CI)

[0.067, 0.217], CFI = 0.594, SRMR = 0.078; Go RT: RMSEA = 0.075, 90% confidence interval (CI) [0.000, 0.160], CFI = 0.873, SRMR = 0.060). Our other two measures showed good fit (functional activity: RMSEA < 0.001, 90% confidence interval (CI) [0.000, 0.111], CFI = 1.000, SRMR = 0.041; attentional control: RMSEA < 0.001, 90% confidence interval (CI) [0.000, 0.106], CFI = 1.000, SRMR = 0.035). We also note that 88 model parameters were being estimated in our model with 104 observations in the Experimental group and 100 in the control group. We replicated all our findings using our LCS models but note caution given bad univariate model fits and a saturated model fit for our quad-variate analysis.

Table S5-1. Criteria for assessing socioeconomic status (SES).

Score	Education	Employment
1	Postgraduate (MSc, MA, PhD) or professional qualification (e.g. law or accountancy training)	Managerial and professional occupations (e.g. company director, head of HR, lawyer, dentist)
2	Undergraduate (BA, BSc) or equivalent (HND/HNC, City and Guilds Qualification, NVQ level 4)	Intermediate occupations (e.g. police officer, administrative assistant, travel consultant)
3	A-level, AS-levels, NVQ level 3, BTEC diplomas	Small employers and own account workers (e.g. interior designer, garden designer, baker)
4	GCSES, CSEs, O-levels, NVQ levels 1 & 2	Lower supervisory and technical occupations (e.g. interior design assistant, finance officer)
5	No formal qualifications	Semi-routine and routine occupations (e.g. yoga teacher, leather crafter, bookseller)

Table S5-2. Sample sizes by each measure, training group and time point

Outcome Measure	Training Group	Pre-test	Post-test	1-year follow-up
SSRT	Experimental Group	114	83	84
	Control Group	112	79	80
	Total	*226*	*162*	*164*
Task-related fMRI	Experimental Group	58	31	-
	Control Group	48	27	-
	Total	*106*	*58*	-
Attentional Control	Experimental Group	115	74	80
	Control Group	106	75	79
	Total	*221*	*149*	*159*

Table S5-3. Correlations of outcome measures

Measures	SSRT Scores	Go RT scores	Functional Activity
SSRT Scores	1.00	-	-
Go_RT scores	-.20*	1.00	-
Functional Activity	.05	-0.10	1.00
Attentional control	0.00	-0.02	.18*

Note: Correlations (*r*) have been shown. Functional activity refers to functional activity in the inhibition network. Correlations significant at *P* <.050 have been indicated with *.

Chapter 6. Effort-related Decision making in childhood

Part of Chapter 6 has been adapted from a published paper: Ganesan, K., & Steinbeis, N. (2021). Effort-related decision-making and its underlying processes during childhood. Developmental Psychology, 57(9), 1487–1496. [*https://doi.org/10.1037/dev0001228*](https://doi.org/10.1037/dev0001228)

6.1. Abstract

Humans tend to avoid cognitive effort. Whereas evidence of this abounds in adults, little is known about its emergence and development in childhood. The few existing studies in children use different experimental paradigms and report contradictory developmental patterns. We examined effort-related decision-making in a sample of 79 5-11-year-olds using a parametric induction of cognitive effort and three paradigms that each involved decision-making between low- and high-effort options but varied in how explicit effort was made. This included a demand avoidance and an effort discounting paradigm. We also probed cognitive processes linked to effort-related decisions, including task performance, metacognitive accuracy, effort perception and mental demand. We found that children of all ages were sensitive to parametric modulations of cognitive effort as indicated by self-report. In terms of effort-related decision-making we found that overall children demonstrated no implicit behavioural preference for low effort tasks, that older children stated a preference for low effort tasks and that all children discounted effort. Further, implicit preference in the demand avoidance paradigm was linked to children's metacognitive insight into how well they could perform effortful tasks. These findings strongly suggest that while children are clearly sensitive to

manipulations of cognitive effort, whether and when they use this information to guide their decisions to engage in effortful tasks depends strongly on the extent to which effortful features are made salient to them.

6.2. Introduction

Humans tend to avoid effort, be it physical or mental (Bonnelle et al., 2015; Kool et al., 2010; Niebaum et al., 2021). Effort is aversive (Dreisbach & Fischer, 2015; Saunders et al., 2018) all else being equal, individuals prefer tasks that make fewer demands (Kool et al., 2010; Niebaum et al., 2021). Prominent theories argue that the aversion induced by effort acts as a value signal forcing individuals to prioritise their goals (Kurzban, 2016; Shenhav et al., 2013, 2016, 2017). It has been shown that willingness to expend effort can account for performance on demanding tasks (Krebs et al., 2010; Kurzban et al., 2013; Umemoto & Holroyd, 2015) which in turn can explain group differences in task performance typically attributed to differences in ability (Foussias et al., 2014; Salamone et al., 2016; Westbrook et al., 2020). Critically, developmental differences on cognitively challenging tasks can at least partly be explained by motivation (Carlson, 2010; Chevalier et al., 2013; Davidson et al., 2006). A better understanding of the nature of developmental change in cognitive abilities therefore requires a thorough assessment of the processes underlying engagement in effortful tasks. Indeed, Chapter 5 highlights the heterogenous nature of training executive functions. Effort exertion and motivation could serve as a mechanism for training gains in both near- and far-transfer measures. Interventions that focus on the optimal use of cognitive control functions rather than focusing on increasing task-related performance may be the way forward. For example, children can be taught strategies that aid in the learning how to gather information to learn if effortful use of cognitive control is necessary, focusing on efficient use of cognitive control. Through this approach, children can use and apply such strategies to multiple domains in their real life, not limited to abilities in the lab. Therefore, understanding effort-related decision making in children may have important implications for future research on executive function interventions.

How the experience of effort affects task engagement has been studied using different methods varying in the degree to which effort is made explicit, namely demand avoidance and effort discounting paradigms. In demand avoidance paradigms subjects choose between task options that differ only in effort level, a feature that is not made explicit. These tasks require monitoring of task demands and coordinating behaviour accordingly (i.e. choosing low effort tasks; Dunn & Risko, 2016; Kool et al., 2010; Niebaum et al., 2021). In effort discounting paradigms on the other hand subjects choose between options that differ explicitly in how much effort is to be expended and how much reward is to be gained. This allows estimating the costs associated with effort (Chong et al., 2017; Massar et al., 2015; Westbrook et al., 2013). Adults have been shown to avoid cognitively demanding tasks (Dunn & Risko, 2016; Kool et al., 2010) and devalue effort (Chong et al., 2017; Massar et al., 2015; Westbrook et al., 2013). It is believed that the same underlying computation may subserve both implicit and explicit effort-related decision-making (Botvinick et al., 2009; McGuire & Botvinick, 2010), but whether these constructs correlate has yet to be tested.

Infants and pre-schoolers readily compute costs associated with actions (Leonard et al., 2017; Liu et al., 2017) and are sensitive to others’ effort and energy expenditure(Leonard et al., 2020) spawning developmental theories on naïve utility understanding (Jara-Ettinger et al., 2016; Lucca et al., 2020; Lucca & Sommerville, 2018). How such computations inform decisions on whether to engage in effortful tasks and how this changes over the course of child development remains unclear however. Using an implicit demand avoidance paradigm, one paper found found that adults and 11-12-year-old children demonstrated a preference for low effort tasks, whereas 6-7-year-old children did not (Niebaum et al., 2021). All age groups performed comparably as indicated by reaction times and accuracy and thus presumably found tasks equally challenging. This suggests that younger children were not yet able to use task-demand signals to coordinate behaviour away from effort. By contrast, a study on the development of explicit effort discounting using an n-back task in 6-12-year-olds found that children devalued effort equally irrespective of age (Chevalier, 2018). One interpretation of these discrepant findings is that children become better at using implicit task demand signals to avoid effort, a requirement that is lessened in the context of explicit discounting paradigms. However, given that at the very core of effort-related decision-making lies a sensitivity to task demands an alternative interpretation is that the specific tasks represent non-trivial features in study design and that these can influence detection of age-related changes. Further, the lack of developmental differences in explicit devaluation of effort (Chevalier, 2018) could be due to the particularly salient operationalisation of effort (i.e. n-back tasks). To obtain convergent results, we based our measures of implicit and explicit effort-related decision-making on the same experimental paradigm, namely an attentional switch task. Crucially, our task employed a fine-grained parametric manipulation of effort (i.e. six effort levels; Chong et al., 2017; Yantis et al., 2002) which arguably possesses greater sensitivity to detect possible age-related changes that might have previously been masked.

One further question relates to the underlying processes of effort-related decision-making in childhood. As candidate processes, we identify 1) task performance, 2) representation of task performance (i.e. metacognition); and 3) effort perception. Task performance is the most frequently studied in terms of its relation to effort decisions, but findings of an association are mixed (Chevalier, 2018; Chong et al., 2017; Niebaum et al., 2021). One other potential factor that could account for effort-related decisions is the *perception* of one's performance rather than actual performance. Given the limits of cognitive resources, it is necessary to ensure the exertion of effort is worthwhile, by weighing up its cost against any associated gains (Kurzban et al., 2013; Shenhav et al., 2013, 2016). Such computations are subserved by metacognitive insight into one's performance and this could be a critical factor in deciding to engage in effortful tasks (Dunn & Risko, 2016). Indeed, younger children have been found to conflate effort exerted with their ability (Muradoglu & Cimpian, 2020; Nicholls, 1978) and metacognitive abilities have been reported to improve with age (Chevalier & Blaye, 2009; Shin et al., 2007). This could account for potential developmental changes in effort-related decision-making, particularly when these are made in the context of implicit tasks. Finally, how effortful a given task is perceived to be (Robinson & Morsella, 2014) could also bias an individual's estimation of costs associated with the exertion of effort. While previous research has found that high effort tasks are perceived to be more effortful (Chevalier, 2018; Chong et al., 2017), it is unclear how such perception may influence effort-related decisions.

In sum, by using a parametric induction of cognitive effort, the present study examined (i) implicit and explicit forms of effort-related decision-making during childhood; and (ii) how alongside age, effort-related decision-making during childhood is related to individual differences in perceived effort, task performance and metacognitive insight into performance.

6.3. Materials and Methods

6.3.1. Participants

Participants were recruited from a school in Greater London, aged between 5.10 – 11.20 years (*M* = 7.91 years, *SD* = 1.57), normally developing and predominantly White. Parental consent was obtained beforehand and the study was approved by the UCL research ethics committee (Protocol number: 12271/001). Testing took place at school with children being tested in pairs. Children were tested apart from each other and wore headphones while completing the tasks. They were told beforehand that they could win gifts ranging in size depending on reward collected during the tasks. Data was collected from 117 children. Due to some unforeseen circumstances, complete data was obtained only from 79 participants (*M* = 8.06, *SD* = 1.58). There were no age differences between those with complete and those with incomplete data (*t* (115) = 1.28, *p* = .202).

6.3.2. Procedure

Participants first completed five rounds of the effort manipulation in the form of an attentional switch task to familiarise them with the task. To examine both implicit and explicit forms of effort-related decisions, we used a demand avoidance paradigm and effort discounting paradigm. The paradigms were administered in the following order: 1. Demand Avoidance: Choice Behaviour; 2. Demand Avoidance: Preference Statement; 3. Metacognition; 4. Effort Experience; 5. Effort Discounting. This order ensured that any findings from the Demand Avoidance and Metacognition paradigms were not confounded by the explicit knowledge of effort differences in each trial or option. Further, the effort experience gave participants the opportunity to experience the different effort levels before making their decisions in the discounting paradigm.

6.3.3. Effort manipulation (Attentional switch task)

A rapid serial visual presentation (RSVP) or attentional switch task was used where cognitive effort was manipulated by changing the number of attentional switches participants had to make. This allowed for a parametric, fine-grained modulation of effort (Chong et al., 2017; Yantis et al., 2002). We adapted the original task to be more child-friendly (i.e. changing numbers and words to images; Figure 6-1a). In our task, participants fixated centrally and had to monitor one of two target streams, each presented on either side of the central fixation. Each target stream was surrounded by three distractor streams. Participants had to respond to a target (i.e. a wand) by pressing the spacebar. A total of three targets appeared per trial. At the beginning of each trial, a direction cue appeared for 4s to indicate which target stream participants had to attend to. During the trial, switch cues (i.e. an owl) were also presented centrally, indicating participants to switch their attention to the opposite side. The number of switches participants had to make was parametrically modulated (i.e. 1-6 times) and varied on any given trial. Each trial consisted of 40 serial presentations, each presented for 350ms. Intervals between switches were pseudorandomised. This task was used throughout as manipulation of cognitive effort the basis of effort-related decisions.

6.3.4. Demand Avoidance Paradigm

6.3.4.1. Choice Behaviour

Participants were introduced to two protagonists, an ice and fire witch, each associated with completing either two or six attentional switches (low or high effort;

Figure 6-1b). The associations between witch and effort level were counterbalanced across participants. Importantly, participants were not told of any differences between the witches. Participants first completed 6 rounds of low and high effort trials each. Following this, participants could choose between the two witches over 30 trials. After each choice, they completed a trial of the attentional switch task that was low (2 switches) or high (6 switches) in effort depending on their choice. The measure of interest was the percentage of trials in which participants chose the low-effort option. Choice behaviour from the demand avoidance paradigm reflects an implicit form of effort-related decision.

Before making their choices, we checked comprehension of the paradigm relating to 1) what objects needed to be collected; 2) how the objects can be collected; 3) how participants know which side of the screen to focus on; 4) what participants should do if the switch cue points to the left; 5) what participants should do if the switch cue points to the right; 6) what participants need to do at the beginning of each round; and 7) which keys needed to be pressed to help each witch. Experimenters were trained beforehand on a range of acceptable responses to these questions that exhibited comprehension of the paradigm. If a participant was unable to provide a correct response, the paradigm was explained once more, and the participant was probed again. All participants passed these validation questions.

6.3.4.1. Preference Statement

After the 30 choices, participants were asked to state which of the two witches they preferred. The preference statement reflects a more explicit form of decision making as participants are asked to report a preference (i.e. subtle cuing; Dunn & Risko, 2016; Kool et al., 2010).

6.3.5. Metacognition Paradigm

To obtain a measure of metacognitive insight into their task performance, participants performed 8 trials of the attentional switch task, half of which required them to make 2 and the other half 6 attentional switches. After each trial, participants rated on a 6-point scale how well they thought they had done (from 'Very poorly' to 'Very well'). Importantly, differences in the number of switches to be made in each trial were not made explicit to ensure this would not confound rating of performance.

6.3.6. Effort Experience Paradigm

Participants performed three iterations of the task at each effort level (i.e. 18 trials). After the experience of each effort level, participants were given a child adapted *NASA Task Load Index* to report perceptions of the task (Laurie-Rose et al., 2017).

6.3.7. Effort Discounting Paradigm

Participants were told that they would be making choices between options varying in attentional switches for which they could win rewards (i.e. tokens). They were told that they would be presented with a series of choices between a baseline option (i.e. low effort, low reward) and a variable option (i.e. high effort, high reward; Figure 6-1c). They were instructed to choose their preferred option and that they would be given a random selection of chosen trials to perform at the end of the experiment. They were told that any tokens earned in this phase would contribute to a gift at the end of the experiment. Participants were presented with a series of 75 binary choices, each with a combination of effort and reward. The baseline option always entailed performing the lowest effort level (i.e. effort level 1) for the lowest reward (i.e. 1 token). The other option presented alongside varied from performing a 2-6 effort level for 2, 4, 6, 8 or 10 tokens. Effort was depicted by a pie chart with different levels and reward was depicted by gems (Figure 6-1c). Order of presentation of the variable options was fully counterbalanced and randomized. Effort discounting was administered as the most explicit form of effort-related decision-making with all task features made highly salient (Chong et al., 2017; Massar et al., 2015; Westbrook et al., 2013)

Before making their choices, comprehension questions were administered relating to 1) what each pie level indicates; 2) what a pie level of 2 indicates; 3) whether participants need to work harder on a game with a pie level of 2 or 4; 4) through which games more gems can be earned - pie level 1 or 5; and 5) what participants can do with the gems they earn. Experimenters were trained beforehand on a range of acceptable responses to these questions that exhibited comprehension of the paradigm. If a participant was unable to provide a correct response, the paradigm was re-explained and the participant was quizzed again. All of our participants passed these validation questions and were included for analysis.

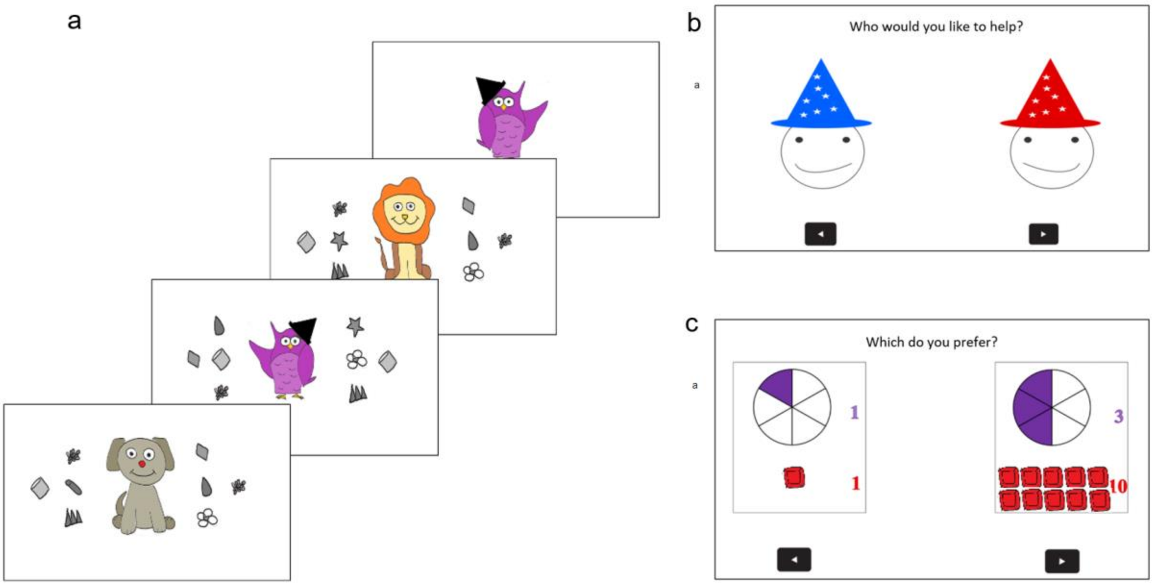


Figure 6-1. (a) Attentional switch task used to manipulate effort. After an initial direction cue, participants had to press the spacebar when a wand was presented and had to make an attentional switch when an owl was presented; (b) Demand Avoidance Paradigm where participants chose the witch they wanted to help followed by a low or high effort variant depending on their choice; (c) Effort Discounting Paradigm where participants chose between a baseline low effort/low reward option and a variable high effort/high reward option.

6.3.8. Statistical Analysis

To examine age-related differences, Pearson's coefficients (*r*) or Spearman's coefficients were reported, where task performance was controlled for in the analysis.

6.3.8.1. Attentional switch: Task Performance

Based on previous studies (Chong et al., 2017), task performance was computed as the overall percentage of trials in the Effort Experience phase where individuals had at least one hit and no more than two false alarms (i.e. *d'* > 2). Previous studies indicate chance performance to be near 0% (Moore et al., 2018). In our paradigm on each trial, there were 40 possible serial presentations on which participants could make a response. Based on this, to estimate chance performance, we simulated random behaviour in 79 agents based on the number of responses made by participants. For example, if a participant made 2 responses on a particular trial, the presentations on which these responses were made were randomly simulated. We compared these responses to presentations on which targets appeared. Using the number of responses made by our participants on each trial as a basis, we simulated a total of 2844 trials. Based on this, chance performance was estimated to be 10%. Using a Repeated Measures ANOVA, we examined the differences in task performance between effort levels.

6.3.8.2. Demand Avoidance: Choice Behaviour

We measured the time taken to make a choice for either of the two options. Age effects were tested by the means of a 2-way repeated measures ANOVA with condition (i.e. low vs high effort) as a within-subjects factor and age as a between-subjects factor. Paired t-tests were used for post-hoc analysis. Choice behaviour was measured by calculating the proportion of low effort trials chosen. To test if choice preference differed from chance, a Wilcoxon signed rank test was used as data was not normally distributed (Shapiro-Wilk normality test; $p < .001$).

6.3.8.3. Demand Avoidance: Preference Statement

We examined the proportion of individuals that stated a preference for low vs high effort task and if this differed from chance using a Wilcoxon signed rank test (Shapiro-Wilk normality test; $p < .001$).

6.3.8.4. Metacognition

Performance (*d'*) was calculated based on the hits (i.e. correct target detection) and false alarms (i.e. response when no target present), according to the following formula: $d' = Z$ (hit rate) $- Z$ (false alarm rate). Based on this, a performance range was calculated and ratings of performance were recoded to this scale. This allowed us to calculate a discrepancy score between actual performance and rated performance (Fleming & Lau, 2014), which in turn was calculated separately for low and high effort trials performed (i.e. four trials each). Signs were removed so that the discrepancy score could indicate metacognitive accuracy. A higher discrepancy score indicated poorer metacognitive accuracy.

6.3.8.5. Effort Experience

The NASA Task Load Index was used to measure perceived effort and mental demand of the task and scores were transformed to a scale of 1 to 10. Using Repeated Measures ANOVA, we examined the differences in perceived effort and mental demand between the 6 effort levels with Greenhouse-Geisser corrections made. As a measure of individual differences in perceived effort and mental demand, a line was fit onto participants' responses for effort levels 1-6.

6.3.8.6. Effort Discounting

The indifference values for each effort level were determined and used to calculate a discounting function for which the area under the curve was computed for each participant (Myerson et al., 2001). Larger values indicate greater degree of effort discounting (Dixon et al., 2006; Lempert et al., 2012; Shiels et al., 2009). Repeated Measures ANOVA was used to examine differences between effort levels and paired t-tests were used to examine differences between each subsequent effort level.

6.4. Results

We examine implicit and explicit forms of effort-related decision-making during childhood and how alongside age, effort-related decision-making during childhood is related to individual differences in perceived effort, task performance and metacognitive insight into performance.

6.4.1. Effort Experience and Task Performance

Overall performance was 53.48% (*SD* = 31.11), which significantly differed from chance (*t* (78) = 12.42, *p* <.001). Performance was constant across number of attentional switches (Figure 6-2a) and there was interaction with age (*p* > .3). Perceived effort increased with the number of attentional switches (*F* (4.21, 185) = 6.79, *p* <.001; Figure 6-2b) and this did not interact further with age (*p* > .6). A similar pattern was observed for mental demand (*F* (4.21, 185) = 8.10, *p* <.001; Figure 6-2c), which also did not interact with age (*p* > .3*).*

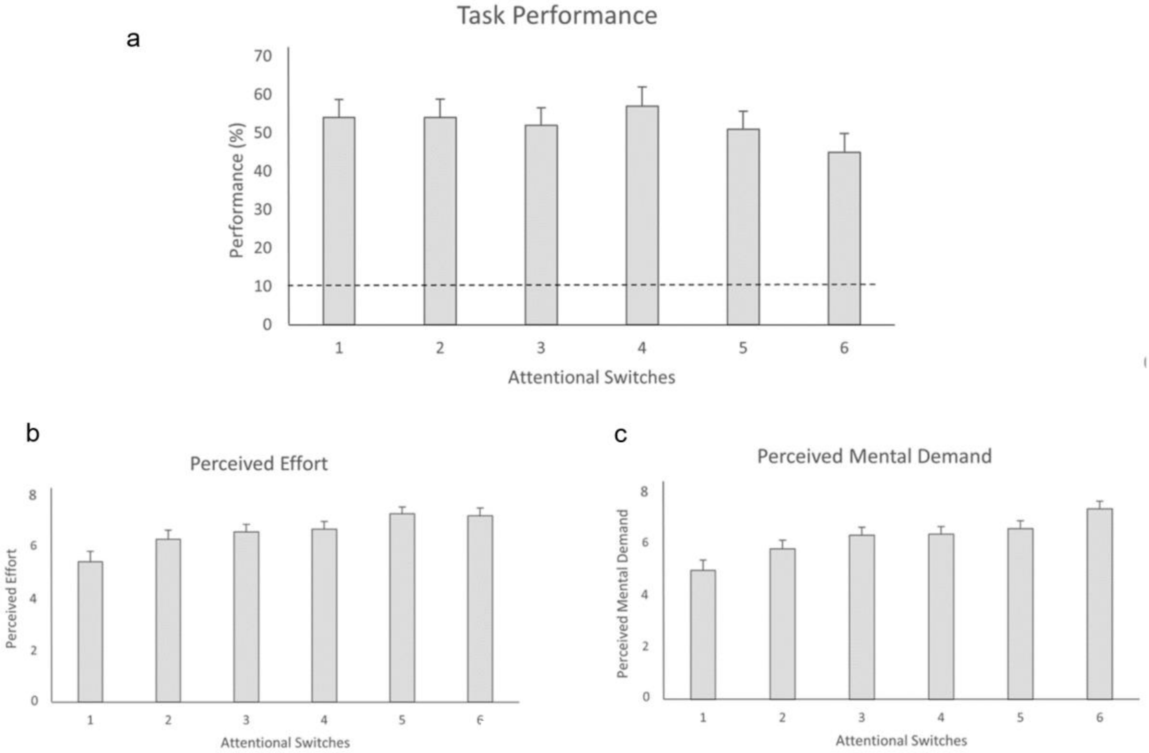


Figure 6-2. Numbers of attentional switches (a) did not affect performance, but did impact (b) perceived effort and (c) mental demand. Dotted line in (a) indicates chance performance.

6.4.2. Demand Avoidance: Choice Behaviour

When analysing reaction times in the demand avoidance task, we found a main effect of Condition (*F* (1, 77) = 3.96, *p* = .05; Figure 6-3b) as well as a significant 2-way interaction between Condition and Age (*F* (1, 77) = 12.60, *p* <.001). Whereas all children took longer to choose the high effort over the low effort option, this effect was particularly pronounced in younger children (*t* (38) = -3.55, *p* <.001). Across the sample, low effort and high effort options were chosen with equal frequency (low effort choice = 47.2%; see Figure 6-3a). This did not change with age (*r* = .15, *p* = .187).

6.4.3. Demand Avoidance: Preference Statement

Across all children, there was no stated preference for either option (low effort preference = 46.8%). This did however change with age (*r* = -.24, *p* = .031; Figure 6-3c), whereby older children increasingly stated a preference for the low effort option. Visual inspection of the data suggests that a switch in preference occurs between 8-9 years. The relatively low numbers in each age group preclude further analysis.

6.4.4. Effort Discounting

There was a significant effect of attentional switches on subjective value (*F* (3.92, 274.68) = 211.86; *p* <.001). This was most pronounced between attentional switch levels 1 and 2 (*t* (74) = 35.83; *p* <.001; Figure 6-3d. Age was not significantly associated with effort discounting (*r* = -.08 *p* = .509).

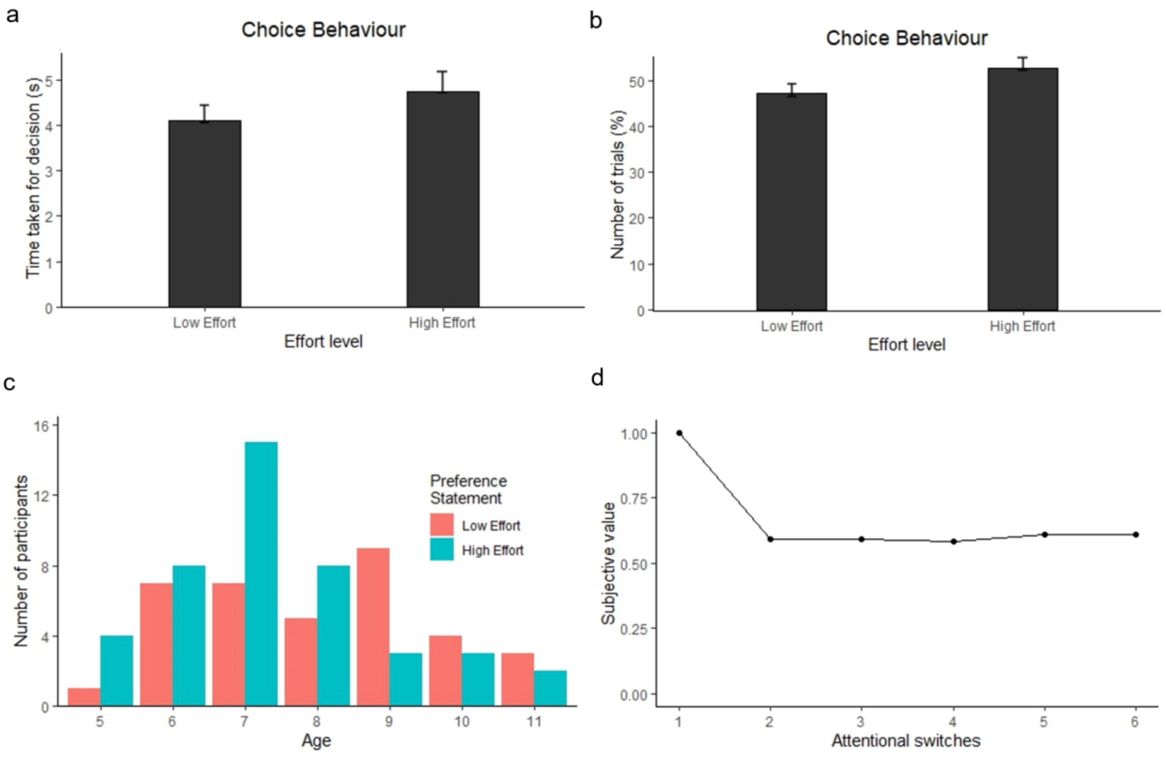


Figure 6-3. (a) There were no difference in proportion of effort options chosen. (b) High effort choices took longer than low effort choices. (c) Stated preference of low vs high effort task was associated with age; (d) Children of all ages significantly discount effort.

6.4.5. Relationships between effort-related decision-making tasks

Choice behaviour and stated preference in the demand avoidance paradigm were significantly correlated (*r* = -.54, *p* <.001), where implicit preference for low tasks was associated with stated preference of low effort tasks. Discounting was marginally correlated, albeit non-significant with both choice behaviour (*r* = -.20, *p* = .094) and stated preference (*r* = .23, *p* = .054) where a higher degree of discounting was marginally correlated with both choice preference and stated preference for low effort tasks.

6.4.6. Age and metacognition

There was a significant association between age and metacognitive abilities on low effort trials (*r* = -.36, *p* = .002) and high effort trials (*r* = -.23, *p* = .051).

6.4.7. Relationships with performance, metacognition and effort perception

Effort-related decisions and age were entered into a multivariate model alongside task performance, metacognition and effort perception. Choice behaviour in the demand avoidance task was associated with metacognitive accuracy on high effort tasks (Table 6-1), where better metacognitive accuracy on high effort trials was related to choosing high effort tasks more frequently than low effort tasks. Further, age remained significantly associated with stated preference for low effort. None of the candidate processes were found to be associated with effort discounting.

Table 6-1. Summary of multivariate models examining the associations between effort decisions, age, task performance, metacognition, and effort perception.

Effort-Related Decision		β (CI 95%)	p-value
Choice Behaviour	Age	.11 (-.03, .25)	.448
	Task Performance	.06 (-.08, .20)	.649
	Metacognition Scores		
	Low Effort	-.18 (-.33, -.02)	.264
	High Effort	.47 (.30, .64)	.007
	Mental Demand	.12 (-.03, .27)	.426
	Perceived Effort	.07 (-.05, .19)	.576
		OR (CI 95%)	p-value
Stated Preference	Age	0.62 (0.42, 0.92)	.017
	Task Performance	1.00 (0.98, 1.02)	.806
	Metacognition Scores		
	Low Effort	0.89 (0.65, 1.24)	.500
	High Effort	0.92 (0.65, 1.30)	.631
	Mental Demand	3.10 (0.67, 14.34)	.146
	Perceived Effort	1.21 (0.46, 3.19)	.706
		β (CI 95%)	p-value
Effort Discounting	Age	-.06 (-.20, .08)	.663
	Task Performance	-.23 (-.37, -.09)	.104
	Metacognition Scores		
	Low Effort	-.19 (-.35, -.03)	.235
	High Effort	.08 (-.09, .25)	.631
	Mental Demand	.01 (-.13, .16)	.923
	Perceived Effort	-.17 (-.29, -.05)	.156

Note: β: beta coefficient value derived from linear regression; OR: (5% CI) – odds ratio derived from logistic regression; CI 95%: 95% confidence interval.

6.5. Discussion

This study used an attentional switch task to parametrically manipulate the experience of cognitive effort and address several outstanding questions in the development of effort-related decision-making in a large sample of children aged 5 to

11 years. We show that our manipulation was successful in inducing concomitant parametric changes in both perceived effort and mental demand across the whole sample. This suggests that our modified version of an established attentional switch task is a suitable paradigm to parametrically induce subjective experience of effort in children. Analysis of effort-related decisions revealed that overall children demonstrated no implicit behavioural preference for low effort tasks, that older children stated a preference for low effort tasks and that children of all ages discounted effort. Finally, individual differences in metacognitive abilities accounted for implicit effort decisions.

We show that our fine-grained parametric manipulation of effort induced analogous changes in perceived effort and mental demand in children. This suggests that attentional switch tasks are a suitable manipulation of subjective effort in children. Such a parametric manipulation benefits effort discounting paradigms that have so far relied on coarser inductions of effort experience (Chevalier, 2018). Having shown that our task can successfully induce the subjective experience of effort in children, we set out to address how children use this to decide whether to engage in a cognitive task or not. Given that subtle differences in tasks are likely to affect both experience of effort and task enjoyment (Puca & Schmalt, 1999), we sought to obtain convergent results by basing different decision-making paradigms on the same experience of effort unlike previous developmental research based on different paradigms (Chevalier, 2018; Niebaum et al., 2021).

We show that children reliably detect differences between high and low effort options in our demand avoidance. In spite of this, and unlike (Niebaum et al., 2021), we do not find any age differences in choice behaviour. This may partly be due to the much lower number of trials in our study (Niebaum et al., 2021), seeing that presumably demand avoidance emerges over time (Kool et al., 2010). Age differences did emerge when children were asked to state an explicit preference. In line with previous research, no age related differences were found in explicit effort decisions (i.e. effort discounting; Chevalier, 2018). Interestingly, although all children discounted effort where they required more reward to perform high effort options, this did not increase parametrically with effort. This is curious as it suggests that despite incremental changes in effort perception and mental demand as a function of effort, unlike in adults (Chong et al., 2017) these do not translate parametrically into children's choices. Effort discounting requires complex computations of integrating the costs of simulated effort exertion and potential reward (Shenhav et al., 2013, 2017) It seems that even though effort is perceived parametrically, drawing on these representations to simulate future effort engagement is less sophisticated in children, especially compared to adults (Chong et al., 2017).

Taken together, the overall developmental pattern across the demand avoidance and effort discounting paradigms suggest that the explicitness of effort is crucial whether and at what point in development effort is taken into account in children's decision-making whether to engage or not. Making effort a salient feature of the decision-making process, as is done in discounting paradigms leads to children as young as 5 years to make choices indicative of a devaluation of effort. Subtler prompts to reflect on effort, such as asking to state a preference, leads to only older children using this feature to inform their decision-making, while in the same children the absence of any reference to effort-related features does not lead to demand avoidance. This suggests that developmental patterns of emergence and change in effort-related decision-making are highly contingent on the salience of effortful features of task structure. Awareness of effort cues has been found to be crucial to effort avoidance (Dunn et al., 2019), while findings on the development of cognitive control have shown that younger children require cues to engage in proactive control, whereas older children can do so unprompted (Chevalier et al., 2015). This strongly suggests that age-related changes in processing of effort-related cues drive both presently and previously observed developmental patterns in effort-related decision-making. Surprisingly, younger children state a preference for high effort tasks when effort cues are present but sparse. It has been shown that younger children tend to more explorative in uncertain environments (Schulz et al., 2019), where in the present case, a high effort task might afford a greater challenge and opportunity to learn (Kool & Botvinick, 2014).

Our findings on the inter-relationships between different effort-related decision-making paradigms are somewhat mixed, with a robust association between implicit choice behaviour and a stated preference in the demand avoidance paradigm, and marginal associations between these two measures and effort discounting. It has previously been argued that effort-related decision-making is a unitary construct subserved by a network of brain regions including the anterior cingulate cortex (Botvinick et al., 2009; McGuire & Botvinick, 2010). Avoiding effort in implicit decisions requires online monitoring demands of several tasks and coordinating behaviour away from high effort tasks (Dunn & Risko, 2016; Kool et al., 2010; Niebaum et al., 2021), whereas effort discounting requires the offline computation of effort costs and weighing this against associated rewards (Shenhav et al., 2013, 2017). This supports the idea of both shared and distinct mechanisms for implicit and explicit forms of effort-related decision-making. We also found that individual differences in metacognitive abilities played a key role for implicit effort-related decision-making. Specifically, better metacognitive accuracy was associated with choosing high effort options. This was surprising as we expected children with better metacognitive abilities to be more sensitive to effort differences causing them to coordinate behaviour away from high effort tasks. One potential explanation is that children who are better able to judge their performance on high effort tasks choose high effort tasks as a strategy to reduce uncertainty (Lee & Coricelli, 2020), choosing tasks where they are better aware of how they are performing in spite of the increased effort exertion required.

Our study has several limitations. Firstly, we did not measure enjoyment of effort. Therefore, we do not know how enjoyable children found our task which may have influenced how costly effort was perceived to be. Task enjoyment might be the most relevant contributor to decision-making especially in the absence of explicit effort cues. Further, individual trait differences in enjoyment of engaging with effort potentially confound our findings (Westbrook et al., 2013) with recent research showing neural networks modulate individual differences in effort seeking vs avoidance (Sayalı & Badre, 2021). Future developmental research should seek to account for both task-specific enjoyment and as well as individual differences in enjoyment derived from engaging with effort (Inzlicht et al., 2018). Further, the present demand avoidance was framed in prosocial terms (i.e. helping witches), introducing social incentives, which might be an additional source of unaccounted variance (Kray et al., 2018). The task battery was designed such that the effort discounting paradigm was placed right at the end. This was done to avoid any influence of explicit knowledge of the effort manipulation on the implicit demand avoidance task. As a result, however, choices in the effort discounting could have been more susceptible to effects of fatigue or boredom (i.e. children could have been less willing to exert effort in the effort discounting paradigm as compared to earlier tasks due to fatigue or boredom. Future work that draws on a wider array of methods to operationalise effort would enable the counterbalancing required to rule out such fatigue or boredom effects that might emerge over time. Further, the extent to which current tasks (i.e. utilising attentional switches, rule switching and working memory; Chevalier, 2018; Chong et al., 2017; Niebaum et al., 2021) are ecologically valid is questionable. Future work may focus on how different real-world contexts and factors interact to influence whether effort is perceived to be costly or as adding value (Inzlicht et al., 2018). Finally, we are unable to rule out experimenter-induced effects. This is less of a concern in our implicit task as experimenters were blind to which task was associated with low or high effort. However, in our explicit effort discounting task both effort levels and reward levels were explicitly cued and therefore, experimenters may have influenced participants to pick options that were deemed more desirable. We tried to counter this by instructing and reassuring participants that they should make selections that they want most and that there are no ‘correct’ or ‘incorrect’ selections. Even with this instruction in place, it is possible that participant choices were biased by the experimenter.

We studied the development of effort-related decision-making in 5-11-year-old children. We used a cognitive task to elicit granular experiences of effort. Based on their experience of this task, children then made decisions on several tasks on whether to expend cognitive effort. These tasks differed in the extent to which effort was made explicit. We show that the extent to which effort is highlighted is a crucial determinant for when children can use this information to guide their decision-making. This developmental pattern fits with literature on the effects of cues on proactive control development. Our account offers a synthesis for previously disparate developmental findings on effort-related decision-making. Future studies should include measures of task-enjoyment as a critical feature of willingness to engage with effortful tasks.

7. General Discussion

Part of Chapter 7 was published in a review paper in Current Opinion in Psychology:: Ganesan, K., & Steinbeis, N. (2022). Development and plasticity of executive functions: A value-based account. Current opinion in psychology, 44, 215–219. https://doi.org/10.1016/j.copsyc.2021.09.012

7.1. Summary of Experimental Chapters

This thesis aimed to investigate the neural correlates of EFs as well as assess its plasticity through training. To do so, a multi-measurement and factor approach was employed to assess EFs, ensuring high validity. Further, randomised controlled trials (RCT) assessing the plasticity of cognitive control were gamified, adaptive and variable which ensured high levels of motivation and engagement amongst children. This ensured that training-related differences between experimental and control groups were not attributed to differences in engagement. Finally, it aimed to clarify previous conflicting findings on effort-related decision making in children which may be crucial to EF performance. In this chapter, I present a summary of the findings and their theoretical implications and limitations. Finally, I outline future directions for the field of cognitive control training.

Chapter 2 aimed to clarify the neural correlates of EFs, which may currently be confounded by measurement impurity issues. To eliminate these issues, a multi-measurement approach to assess EFs was taken. Further, we differentiated between age-dependent and age-independent neural correlates of EFs. Age-dependent associations may point to brain maturation over a developmental trajectory that mediate gains in EFs while age-independent associations may indicate crucial individual differences in cortical thickness that are associated with EF abilities. While neural correlates of working memory and shifting were identified, no neural correlates were observed for inhibition. Age-dependent neural correlates of working memory were identified, suggesting that maturation of these regions plays a role in mediating gains in abilities. In contrast, age-independent neural correlates of shifting were identified, suggesting that individual differences may be particularly important in predicting shifting abilities.

Chapter 3 aimed to clarify the mechanism which may underlie cognitive control by leveraging a training design. Specifically, a RCT was used to examine how training inhibition vs context monitoring led to improvements in measurements of cognitive control. Whereas all children improved in the targeted cognitive functions over the course of training, pre-post data show that only the inhibition group improved on cognitive control indicies. Our findings show a privileged role of inhibition in childhood cognitive control.

Chapter 4 aimed to examine transfer to other EFs through a training protocol employing inhibition. We used a gold-standard training protocol and assessed EFs through a multi-measurement approach. Additionally, we looked at error rates and reaction times separately, hypothesising that it would give us a more fine-grained understanding to EF transfer. Although no training-related improvements in error rates were observed, strategic slowing was observed in the experimental group. Our findings potentially point to a mechanism through which inhibition-based training may operate.

Chapter 5 examined the extent to which cognitive control training could produce far-transfer into a real-world measure. Our gold-standard cognitive control training protocol was used to specifically assess transfer into parent-reported measure of attentional control. Additionally, we examined whether individual differences in brain-behaviour measures may predict far-transfer. As expected, sustained training-related changes in cognitive control were found. Strikingly, in the experimental group, improvements in parent-reported attentional control were reported. These improvements were predicted by decreases in functional activity in the inhibition network. Additionally, baseline functional activity in the inhibition network also predicted far-transfer to attentional control at post-test and follow-up. Our findings point to the necessity of looking at individual differences in gains associated with cognitive control interventions.

Finally, Chapter 6 examined how children may avoid effort exertion. While overall children demonstrated no implicit behavioural preference for low effort tasks, older children stated a preference for low effort tasks. When effort was made a salient feature, children of all ages discounted effort. Finally, individual differences in metacognitive abilities accounted for implicit effort decisions. Our findings offer an integrative account of effort-related decision making across tasks with subtler to more explicit cues. These findings are a first step in understanding effort exertion amongst children, which could provide insight into performance on effortful cognitive control tasks.

7.2. Theoretical Implications and limitations

As discussed in Chapter 1, cognitive control/executive functions play a crucial role in supporting everyday goals and behaviour. In the experimental setting, measurements of EFs are heavily confounded by other abilities (e.g. lexical, comprehension). Therefore, it is necessary for a multi measurement approach to be taken where factors of EF can be calculated. Further, attempts to boost cognitive control have been heavily impacted by methodological issues that contribute to low engagement amongst developmental populations. The aim of this thesis was to build upon these issues to confidently examine the neural correlates of EFs, identify a mechanism for training and investigate the extent of transfer possible through training. Based on the findings from this thesis, I discuss the theoretical implications for the field of EFs and cognitive control training.

7.2.1. Unity and Diversity

Often, in fulfilling our goals the three EFs (i.e. inhibition, shifting and memory) work in unity with clear parallels observed between them (Baddeley, 2012; Dajani & Uddin, 2015; Munakata et al., 2011). Indeed, as discussed in Chapter 1, The model of unity and diversity states that while the functions of EFs are separable they share commonality (Karr et al., 2018; Miyake et al., 2000; Miyake & Friedman, 2012). However, inconsistent findings in the literature in support of this theory could potentially be heavily confounded by measurement impurity issues (Collette et al., 2006; Miyake et al., 2000; Miyake & Friedman, 2012; Snyder et al., 2015). For instance, measures of inhibition may be confounded by task-specific abilities (e.g. comprehension) or even by the other EFs. This extends to the literature examining neural correlates of EFs – where inconsistent findings could be attributed to task-impurity. Therefore, we build on these methodological issues in examining support for the unity and diversity theory.

In line with this theory, using a multi-measurement approach, separable functions of EFs were yielded in Chapter 2. However, we do note that in Chapter 4, a two-factor and unitary factor were found when examining indices of error rates and reaction times respectively. Indeed, in the literature the use of error rates and reaction times as proxies of EF performance has been inconsistent (Huizinga et al., 2006; Messer et al., 2022; Scionti & Marzocchi, 2021; Völter et al., 2022). This may also explain inconsistent yieldings of 1-3 factors of EF, especially in a developmental population (Huizinga et al., 2006; Karr et al., 2018; Messer et al., 2018).

Additionally, examining the neural evidence in Chapter 2, lends support for the unity and diversity theory and the role of inhibition. Specifically, distinct neural regions were found to be associated with shifting and memory. However, we note no neural correlates of inhibition were identified. In our method of using a factor analysis, we isolate unique factors of EFs (i.e. inhibition factor represents inhibition purely where overlap between other EFs excluded). This suggests that inhibition is not uniquely associated with any neural correlates and may point to it representing general executive functioning (McKenna et al., 2017). This is line with previous theories considering inhibition to be at the core of EFs (Aron, 2007). Inhibition emerges early and has been reported to be the first EF to develop (Fiske & Holmboe, 2019; Hendry et al., 2022), as shown both in young children and infants (Best et al., 2009; Best & Miller, 2010; Friedman et al., 2011; Garon et al., 2008, 2013; Topál et al., 2008). In support of this, a meta-analysis found that activity underlying inhibition was completely overlapping with general executive functioning (McKenna et al., 2017). Our findings help clarify the organisation of EFs and in particular the role of inhibition.

7.2.2. Mechanism for cognitive control training

The evidence in relation to the unity and diversity model builds nicely in uncovering an appropriate target mechanism for training. In Chapter 1, we discussed how mixed evidence relating to interventions targeting working memory and shifting may be due to interventions unsuccessfully tapping into a common mechanism underlying EF (Kassai et al., 2019; Sala & Gobet, 2017). This suggests that the target mechanism employed by training interventions is not trivial, and could determine training success. Given that inhibition may represent common executive functioning (Chapter 2; Aron, 2007; McKenna et al., 2017), it may be promising as a target mechanism compared to other EFs.

However, recent accounts have argued that context monitoring may be a more relevant mechanism for training (Chatham et al., 2012; Dodds et al., 2011; Hampshire et al., 2010). Arguably, for instance, the ability to inhibit unwanted thoughts or actions depends on monitoring the environment for contextual cues that indicate the need to change action (Chatham et al., 2012; Dodds et al., 2011; Hampshire et al., 2010). Evidence surrounding inhibition-based interventions and context monitoring-based interventions have shown promise, although studies are confounded with some methodological problems that put findings into question (Berkman et al., 2014; Chevalier et al., 2014). Using a gold-standard randomised controlled trial (RCT) where training was engaging for both groups, in Chapter 3 we aimed to solve previous inconsistent accounts. Looking at multiple measurements of cognitive control, we examine only training-related improvements in the inhibition group. This suggests that training context monitoring alone is insufficient and needs to be paired with motoric inhibition for pre-post training improvements. Further, our findings reinforce inhibition as a crucial mechanism underlying cognitive control and suggest that inhibition-based training holds promise.

7.2.3. Cognitive Control training design

While attempts to improve cognitive control have produced mixed results, we hypothesised that part of this could be attributed to training design (Smid et al., 2020). In particular, engagement and motivation may be crucial to training improvements. Current training attempts may be confounded by this where lack of training improvements are simply attributed to low engagement or motivation, given the effortful nature of training tasks (Botvinick & Braver, 2015). Additionally, motivation to perform training games may not be comparable between the groups where administered protocols for the control group are not engaging. Therefore, it is necessary to build a training regime that keeps engagement and motivation high for both groups (Johann & Karbach, 2020; Smid et al., 2020). On this basis, in Chapters 3, 4 and 5, we address this by using a gamified training paradigm. Further, an adaptive protocol was adopted to ensure that training was challenging enough for the children to keep them motivated, but not too difficult that it reduced engagement. Indeed, with these stipulations, in our training design (Chapters 3, 4, 5) motivation was high and comparable between experimental and control groups.

Additionally, adopting an adaptive design allowed us to eliminate any ceiling effects that could occur. Theoretically, this ensured that children with all abilities could reap benefits from the training intervention (though see importance of baseline abilities in Section 7.2.4.3.). Finally, it is crucial that interventions adopt a variable design (with different contexts) as this has been found to be important for learning and generalisation. Indeed, our variable training protocol ensured that all training groups improved on their respective cognitive functions through the training (Chapter 3, 4, 5).

Creating a training design on this gold-standard protocol allowed us to interpret training group differences confidently, eliminating any task-related design issues that may confound observed improvements. Any lack of training improvements could also be confidently interpreted as real observations rather than confounded by training design.

7.2.4. Cognitive Control training success

Using this protocol, eliminating any task or design related confounds, we examined the plasticity of cognitive control. We consistently find that cognitive control can be trained (Chapter 3 and 5), with these effects maintained at 1-year-follow-up (Chapter 5). This is in line with previous research where near-transfer effects have been reported (i.e. improvements observed in domain trained; Podlesek et al., 2021; Sala & Gobet, 2017). In this section, we look at whether cognitive control training produces transfer into other EFs and other domains.

7.2.4.1. Transfer into other EFs

In line with the Unity and Diversity model (Miyake et al., 2000), we expected transfer to other EFs occurs. In particular, given that inhibition may tap into common mechanism of EF, we hypothesised that it should produce transfer into other EFs. Additionally, we examined indices of error rates and reaction times separately – theorising that they may provide us with more fine-grained information (de Boeck & Jeon, 2019). Indeed, patterns of training-related improvements differed depending on indices examined. While no improvements in error rates were observed, changes in a unitary factor of strategic slowing were observed. Specifically, increases in strategic slowing were found in the experimental group as a function of the training.

However, these changes did not predict any improvements in error rates. Therefore, the utility of this slowing is questionable. Future directions regarding this lack of utility have been discussed in Section 7.3.5. In conclusion, our findings show that indices used to measure EFs are not trivial. Chapter 4 suggests that our cognitive control training employing inhibition has particularly trained strategic slowing. This gives us fine-grained insight into the exact processes inhibition-based training may target, demonstrating the benefits of examining indices of errors and reaction times separately.

7.2.4.2. Far Transfer

The literature on far-transfer suggests that while cognitive control training is effective at improving domains that have been trained, producing transfer into real-world outcomes is difficult (Sala & Gobet, 2017). The evidence in the literature has been confounded by design related issues. Given the likelihood of small effect sizes, criticisms have focused on small sample sizes, as well as training regimes lacking core features minimally required for far transfer (Diamond & Lee, 2011; Moreau & Conway, 2014; Raviv et al., 2022), such as variability, diversity and complexity of input. Further, training mechanisms appear to be poorly specified (Gobet & Sala, 2022; Shawn Green et al., 2019; Smid et al., 2020) with poor training designs. In Chapter 5, we specifically looked at attentional control rated by parents. Strikingly, we find improvements in attentional control in the experimental group. This suggests that cognitive control interventions employing inhibition hold promise for far-transfer.

Additionally, attentional control has a crucial role in academic and social settings as well as for health (Derakshan & Eysenck, 2009; Normand et al., 2014; Rueda et al., 2010), further demonstrating the promise of our findings.

However, we note that far-transfer to functional activity in the inhibition network was not found (Chapter 5). A previous study in adults employing inhibition have found pre-post changes in the inhibition network. Especially in our cohort of children, our functional MRI data may have been particularly susceptible to noise, where children have a harder time maintaining their attention during the task in the scanner.

7.2.4.3. Individual Differences

While Chapter 5 shows promise for cognitive control interventions, it also suggests that training gains are highly variable. In particular, even with an adaptive training protocol, training gains are highly dependent on individual differences. Looking at far-transfer of attentional control, Chapter 5 finds that neural regions underlying the inhibition network plays a crucial role in predicting far-transfer. Generally, we find evidence for compensation effects suggesting that interventions are most effective for those who start with poorer abilities (Könen & Karbach, 2015; Traut, Guild, et al., 2021). Additionally we find that changes in functional activity predicted training-related changes in attentional control. Specifically, decreases in functional activity in the inhibition network predicted improvements in attentional control. This lends support to cognitive control cognitive training altering neural efficiency of cognitive control processes (Adibi et al., 2013; Bonnasse-Gahot & Nadal, 2008). Our findings reinforce the notion that examining training interventions from the point of view of individual differences can hint at mechanisms of training transfer.

7.2.4.4. Maintenance

While we were able to produce maintenance at 1-year-follow-up in cognitive control itself, maintenance of far-transfer in attentional control was not found (Chapter 5). Despite previous findings suggesting that motivation is key to maintenance (Johann & Karbach, 2020), we find maintenance to be limited to near-transfer. However, we note that individual differences (i.e. in brain indices) were particularly crucial in maintaining far-transfer effects. Our findings reinforce previous findings that maintenance of training effects through experimental training paradigms is difficult. Arguably, as discussed in Chapter 1, achieving maintenance should be key for interventions, ensuring that benefits are not short-lived. Hence, if maintenance of far-transfer cannot be achieved through current training methods, a different approach to training may be needed which we discuss in Section 7.3.4.

7.2.5. Effort-related decision making

Finally, we examined how children avoid effort. This is particularly relevant to EFs, where performing EF tasks is incredibly cognitively demanding (Botvinick & Braver, 2015). While there is abundant literature on effort avoidance in adult populations, this phenomenon in children is relatively unstudied. The couple of studies that do exist show conflicting findings (Chevalier, 2018; Niebaum et al., 2021). Part of this, may be due to methodological differences in tasks – with effort cues varying in their level of saliency. Specifically, for instance in demand avoidance tasks, participants choose between task options that differ only in effort level, a feature that is not made explicit (Dunn et al., 2016; Kool et al., 2010; Niebaum et al., 2018). In contrast, effort discounting paradigms make effort-reward associations clear (Chong et al., 2017; Dunn & Risko, 2016; Massar et al., 2015; Westbrook et al., 2019).

Indeed, in Chapter 6, we find that this is not a trivial feature. While all children discounted effort, only older children were able to use implicit cues to state a preference for a low demand option. These findings are crucial in understanding and reconciling previous literature on effort avoidance in children. Further, we note that metacognitive insight was linked to implicit preference. Specifically, better metacognitive abilities on high effort tasks were associated with choosing high effort options. This was counter to our hypotheses where we expected children with better metacognitive abilities to be more sensitive to effort differences causing them to coordinate behaviour away from high effort tasks. However, one potential explanation may be that children who are better able to judge their performance on high effort tasks choose high effort tasks as a strategy to reduce uncertainty (Lee & Coricelli, 2020). These findings are an important step in understanding effort-related decisions in children which could change the way we conceptualise EFs.

7.2.6. Summary

This thesis builds on previous methodological issues relating to the measurement of EFs and training designs. Our findings show promise for cognitive control training based on inhibition, with far-transfer observed. This marks an important step for cognitive control training where far-transfer has been difficult. This may emphasise the need for gold-standard training protocols in maximising intervention gains. Notably, individual differences in brain-behaviour indices were crucial in predicting far-transfer. This highlights the heterogeneous nature of training gains and the need to examine training gains from an individual differences perspective. However, maintenance of training improvements remains an issue even with a gold-standard protocol. This suggests that a different approach to examining EFs needs to be taken. In a first step to this, this thesis clarified the nature of effort exertion in children.

7.3. Limitations and Future Directions

7.3.1. Individual differences

In line with previous research, we found that training effectiveness depends on individual differences (Chapter 5). Specifically, this could depend on a range of brain-behaviour indices (i.e. not just restricted to domain being measured). In Chapter 5, specifically, we examined how behavioural and neural indices of inhibition could predict improvements in attentional control. Future, studies could potentially leverage on collecting a battery of experimental, neural and questionnaire-based measures to build a multi-measure model to understand training effectiveness in a more holistic way. As expected, we find evidence for a compensation effect. In line with the literature, this suggests that interventions are largely more effective for children with poorer EFs at baseline (Karbach & Unger, 2014; Traut, Chevalier, et al., 2021; Traut, Guild, et al., 2021). Should interventions be restricted to children with poorer EFs? Future research should explore if there is a possibility to boost cognitive control further in children with high baseline EF abilities. Technically, in this thesis (Chapter 3-5), as the cognitive control training design employed was adaptive, children with better EF abilities at baseline should have been able to benefit equally as those with poorer EF abilities. It could be possible that a different strategy of training may be more beneficial for children with high EF abilities. Could personalised interventions be a plausible direction? For instance, one paper found that individuals with lower proactive control to maximally benefit from a specific training condition, suggesting that interventions could use these individual profiles to personalise training (Traut, Chevalier, et al., 2021). Here, again having a holistic understanding of individual differences in predicting intervention effectiveness could be useful in building individual profiles and matching interventions. However, I note that the execution of this in a real-life setting may be implausible, placing a huge burden on schools and teachers.

7.3.2. Considerations relating to training effectiveness

Here I discuss two main considerations for training effectiveness: far-transfer and maintenance of improvements. Chapter 5 shows promise for cognitive control training in producing far-transfer to attentional control. However, I recognise the limitations in my assessment of far-transfer. Indeed, Chapter 5 focused on a singular measure of real-life outcome. What about other domains of transfer or other contexts? For instance, it is unclear if transfer to other domains such as emotional wellbeing can be produced. Arguably, cognitive control mechanisms like emotional regulation may be more relevant for transfer to outcomes such as depression and anxiety (Gustavson et al., 2018; Hsu et al., 2015).. This would suggest that then, for instance, interventions may need to ensure that emotional regulation is targeted through training to maximise outcomes related to emotional wellbeing (Gustavson et al., 2018; Hsu et al., 2015). Additionally, these different contexts in which EFs may need to be utilised suggests that training needs to be contextualised for other real-life domains (i.e. ecologically valid setting). For example, to maximise better mental health outcomes training may have to employ cognitive control functions in an affective context. Interventions with multi-faceted training components have shown promise (Griffiths et al., 2020) but future research is needed to understand its efficacy in improving childhood cognitive control.

Further, this thesis finds maintenance of training-related improvements (far-transfer) to be difficult. We find that again individual differences may be crucial to this, in line with the compensation effect. This huge variability may suggest that future research should examine how maintenance in far-transfer in particular can be maximally achieved. One possibility may be to administer ‘booster’ sessions (i.e. training administered again at a later time point to sustain improvements). This raises questions about the frequency and intensity of these sessions which future research should investigate. It should be noted that if we only see maintenance with the implementation of consistent ‘booster’ sessions, then the plausibility of this should be questioned as the administration of booster sessions consistently throughout childhood may not be practical solution (Section 7.3.5).

Overall, this thesis highlights the issues surrounding cognitive control training and perhaps a different approach focusing on the utilisation of EFs may help with maintenance and breadth of far-transfer.

7.3.5. Speed-Accuracy Trade-offs

Our findings from Chapter 5 suggests that despite composite measures of speed and accuracy in the context of EF abilities, these indices may reflect different processes. Future research is necessary in careful disentangling this relationship. For instance, while slowing of responses could indicate a strategy to allow individuals to careful consider their responses to maximise accuracy, it could also be indicative of lack of motivation or lapses in attention (Domingue et al., 2022). Part of this contradiction makes it hard to accurately look at the utility of slowing. Future experimental research is necessary in carefully disentangling these factors. Previously pupil dilation has been used as a proxy for motivation or effort, which could help account for motivation related factors (Shechter & Share, 2021; van der Wel & van Steenbergen, 2018). Additionally, drift diffusion modelling could be used to model lapses in attention helping to disentangle the relationship between speed and accuracy (Coyle, 2017).

We should consider though that perhaps the relationship between speed and accuracy is highly dependent on individual differences. For instance, some children may just be more likely to give incorrect and slower responses. Other children may instead use strategic slowing to increase their accuracy. While this remains a possibility, arguably this could be accounted by mechanistic accounts rooted in attention allocation and proactive control (Domingue et al., 2022). Nevertheless, future research should examine individual differences in the speed-accuracy trade-off more carefully.

Finally, one crucial factor to consider is the context of our training. While our experimental group were arguably trained on slowing down strategically, it is perhaps necessary to train children on contexts on which this strategy may be useful. Indeed, in Chapter 5, we find that while slowing down helped accuracies on some tasks, the opposite pattern was observed in other tasks. Therefore, without teaching children contextual utilisation of strategic slowing, it may be difficult to see its benefits (as it may be blindly applied across all contexts).

7.3.4. Valuation-based account

The issues surrounding far-transfer, maintenance, and employment of strategies suggest that a different approach to cognitive control interventions needs to be taken. Therefore, in particular, there needs to be more focus on the utilization of EFs rather than training specific skills.

In Chapter 1, we discuss viewing EFs through a valuation-based framework. Specifically, viewing EFs less as abilities but rather as being heavily dependent on resources that are deployed depending on context (Qu et al., 2013; Tarullo et al., 2018). Based on a cost-value computation of effort exertion, individuals may make a decision as to whether exertion of effort is worthwhile (Shenhav et al., 2017), explaining poorer performance on EF Tasks. In line with this, in Chapter 6, we find children of all ages to be effort avoidant, especially when effort cues are made explicit. This could have huge implications for cognitive control interventions. It is possible that incentives offered for task performance do not adequately offset effort costs associated with EF tasks (Chevalier, 2018). Therefore, children in particular may choose not to exert effort in EF tasks, given the limited cognitive resources available to them. Such rational allocation of limited resources could be interpreted as poor abilities. Indeed, Chapter 6 reinforces this, finding that children are effort avoidant especially when effort cues are made explicit.

A recent account puts forward the Learned Value of Control model, which suggests that individuals estimate the value of exerting control based on the features of an environment (Lieder et al., 2018). Specifically, it states that individuals gather information from their environment to estimate the degree to which control should be allocated (Lieder et al., 2018). For example, individuals have been shown to learn to exert more control after their performance was rewarded (Braem et al., 2012). This shows that individuals are able to use changing information in the environment and integrate them, dynamically adjusting their behaviour. This account poses a plausible framework for how children learn the cost-value associated with exerting control.

Perhaps, this may be key in designing interventions aiming to improve EF abilities. Instead of training competencies, training interventions could instead focus on such associative learning strategies that rely on accumulation of information to learn if effortful control is necessary. This more mechanistic approach could potentially have better success in transfer to all domains of EF as well as real-life transfer. The aim of an intervention aimed at boosting EFs should therefore not necessarily focus on simple quantitative increases in improvements (i.e. greater working memory span; faster stop signal reaction times), but rather target the optimal use of executive functions, such as increasing the efficiency with how limited resources can be used to obtain desired outcomes.

7.3.5. Resource considerations

Ultimately, training cognitive control is an effortful endeavour. Therefore, it is crucial to optimise training-regimes to be maximally beneficial before implementation in schools could be rolled out (Kray & Ferdinand, 2013). Indeed, there are resource considerations to consider in the designs of interventions. For instance, training regimes need to be easy to administer, ensuring that this does not require schools to set aside time to intensively train teachers to be able to administer protocols (Schonert-Reichl et al., 2015). This may indicate that training protocols should have clear instructions and a clear flow that is comprehensible to children (without needing too much additional help). Given limited time in schools, we would want to ensure training is appropriate in length and frequency and does not interfere with other important academic learning.

Given this, there are some crucial considerations for far-transfer and maintenance. For instance, if for maintenance effects to be observed, frequent ‘booster’ sessions need to be administered then the plausability of cognitive control training is questionable. Similarly, if far-transfer to other contexts and domains can only be produced if training occurs in a multitude of environments, this may pose too much of a time burden. Therefore, it is necessary to weigh out the resources needed for interventions to take place vs the (potential) benefits of interventions.

7.3.6. Summary

Future research needs to focus on the far-transfer and maintenance of training effects, looking at this from an individual difference perspective. The many issues that cripple the field of cognitive control training suggest a more value-based approach needs to be taken. Specifically, training children on the optimal use of EFs rather than training specific skills or abilities. Administering interventions is a ambitious and effortful endeavour, therefore the cost-benefits of interventions need to be carefully weighed up.

7.4. Conclusion

The aim of this thesis was to examine the neural correlates of EFs and its plasticity through cognitive control training. Additionally, this thesis aimed to provide a first step into looking at effort-related decisions in children. Using a multi-measurement approach to assess EFs, this thesis clarifies the neural substrates underlying the three EFs (inhibition, working memory and shifting). Further, through a gold-standard training protocol, we found that inhibition may hold promise as a target mechanism for training. In the experimental group, selective transfer to EF indices of reaction times were found, as well as far-transfer to attentional control. These findings provide mixed support for the effectiveness of cognitive control training, with maintenance of improvements in particular posing to be an issue. Finally, we clarify previous research on effort-related decisions in children, finding that while children of all ages avoided effort, younger children were only able to do so when effort cues were made explicit. This thesis serves as important groundwork to understand the effectiveness of current training interventions and provides recommendations for paths forward.

8. Supplementary Figures

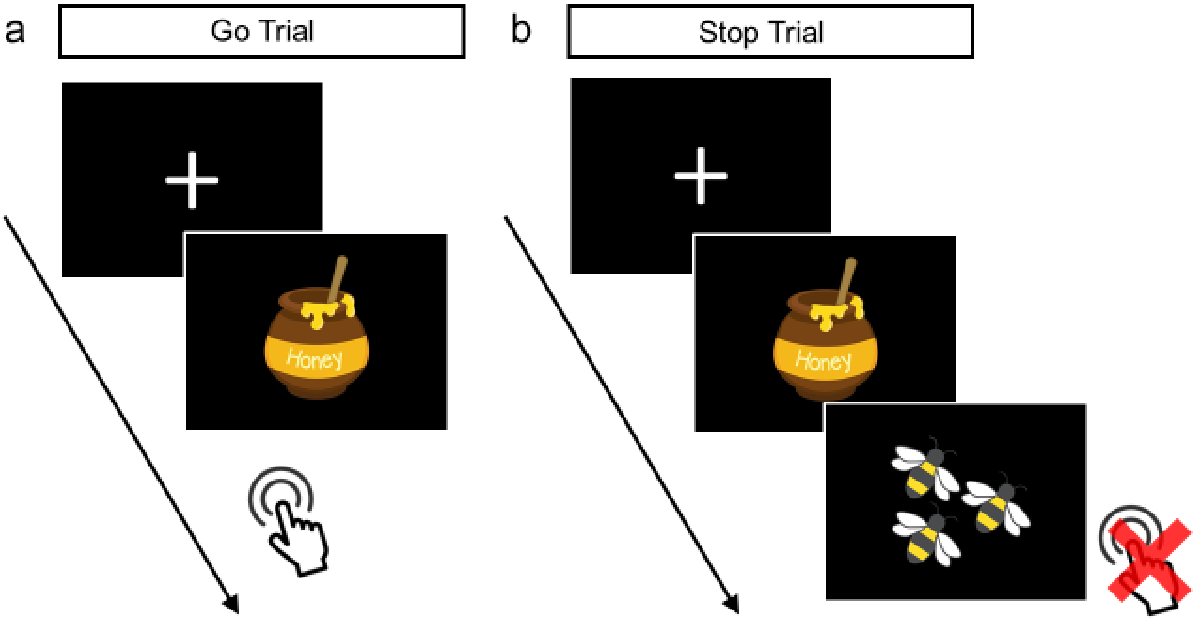


Figure S-1. Stop Signal Reaction Time (SSRT) task where on 'go' trials (a, participants were to make a response as fast as they could. On 'stop' trials where the 'stop' signal was presented (i.e. bees) participants were instructed to make no response.

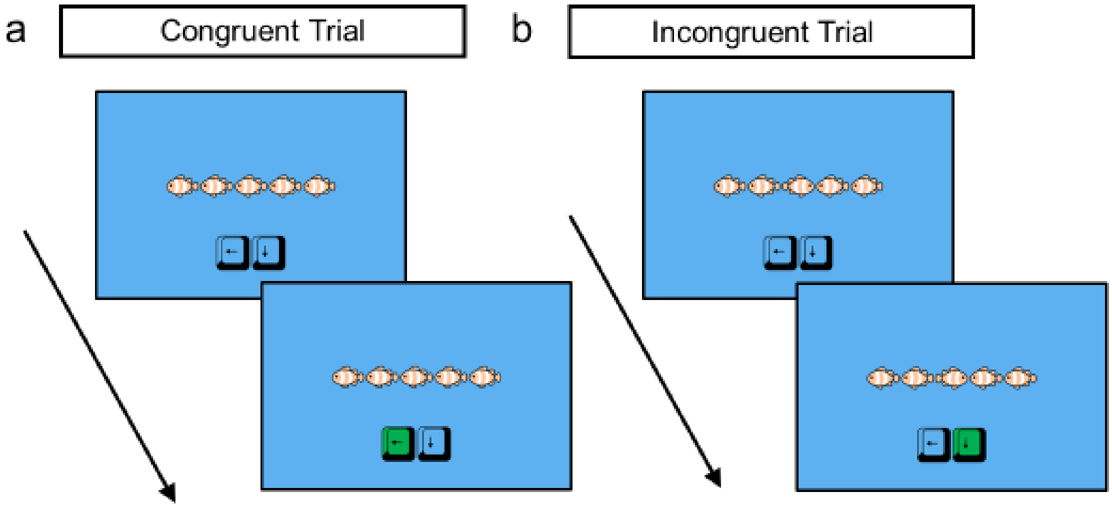


Figure S-2. Flanker inhibition task where participants had to indicate the direction of the middle fish (i.e. central target). During congruent trials (a), the central target stimulus faced the same direction as the other stimuli. During incongruent trials (b), the central target stimulus faced the opposite direction to the other stimuli.

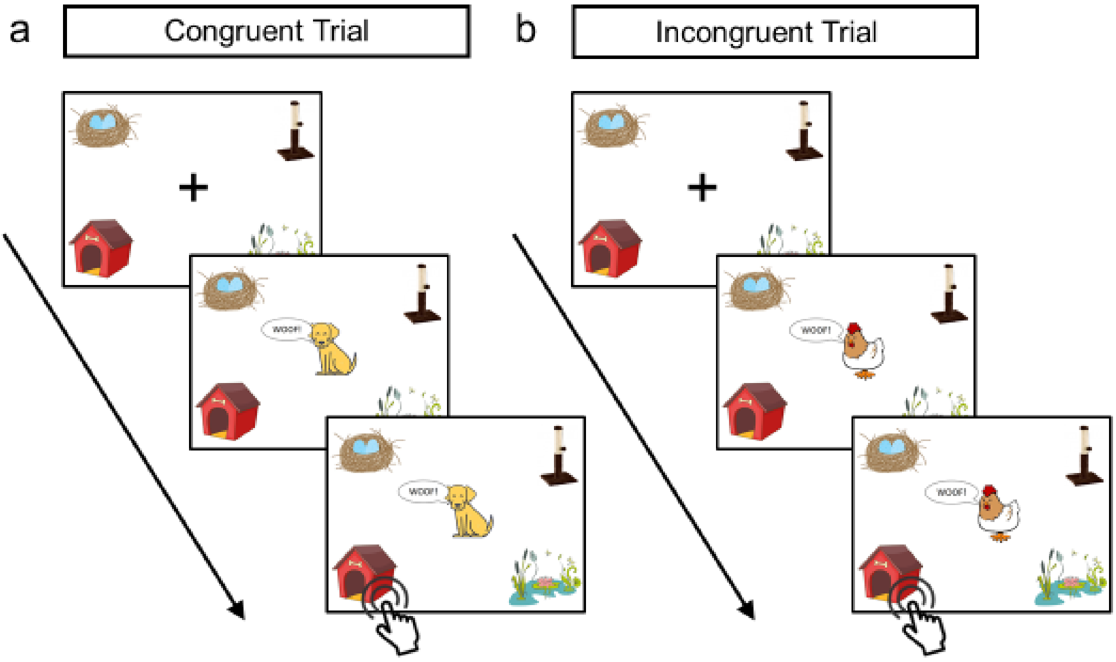


Figure S-3. Animal Stroop task where participants were told match the animal (based on auditory stimuli) to its home. On congruent trials (a) the visual stimuli of the animal matched the auditory stimuli. On incongruent trials (b) the visual and auditory stimuli did not match.

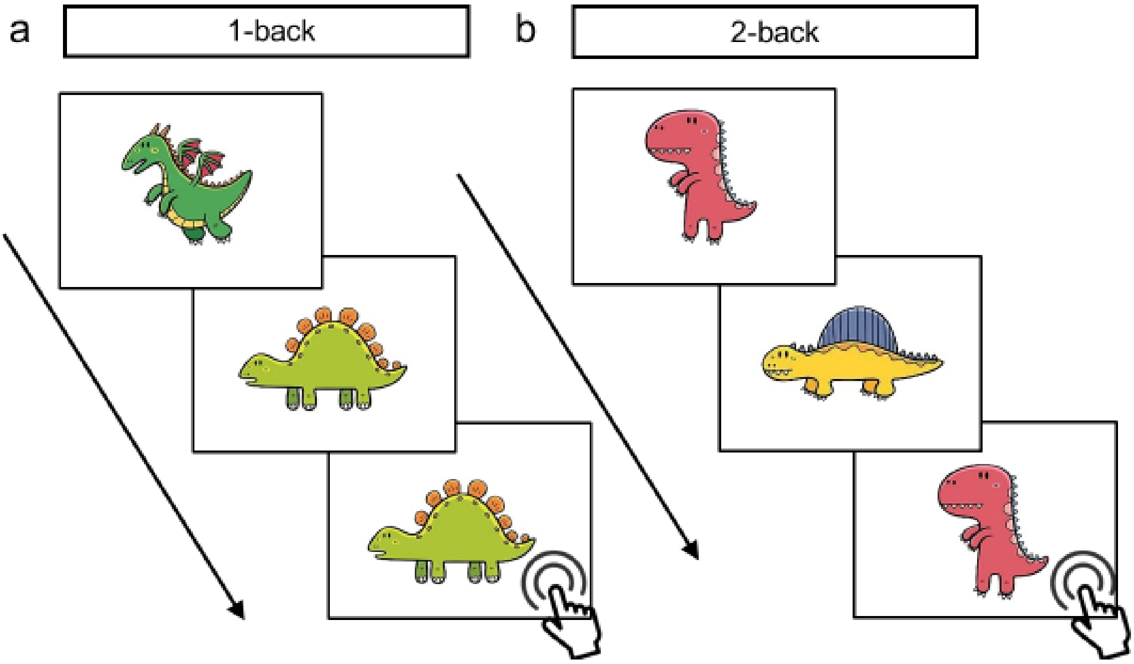


Figure S-4. N-back task where participants completed two variations (1- and 2-back). During the 1-back task, participants had to respond by pressing the spacebar if they saw the same dinosaur twice in a row. During the 2-back block (b), participants had to respond by pressing the spacebar if the current dinosaur was the same as two stimuli previously.

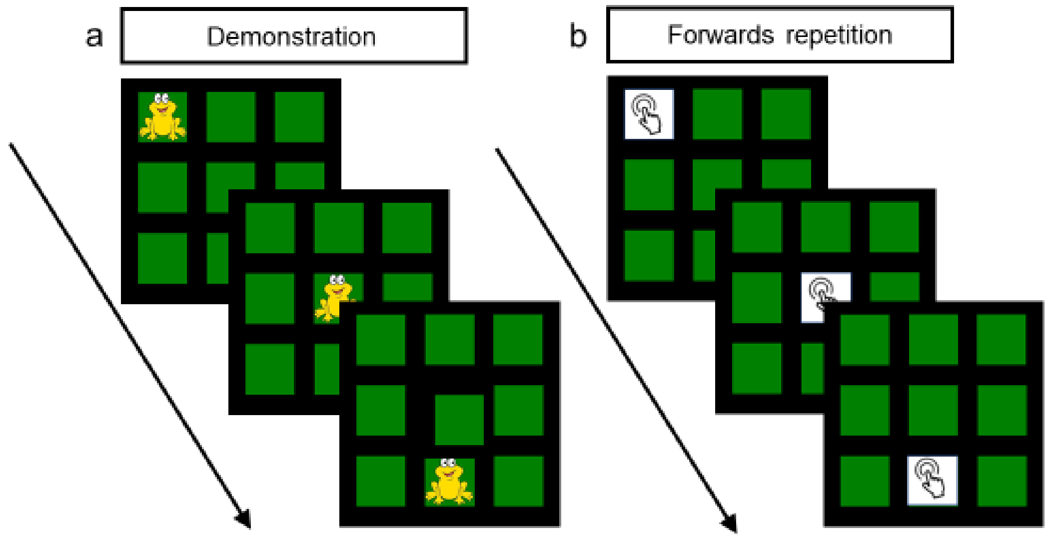


Figure S-5. Corsi block tapping task where on each trial (a), participants first observed the target stimulus ‘jumping’ between lily pads. Then participants were required (b) to repeat the sequence of ‘jumping’ by clicking on the correct lily pads.

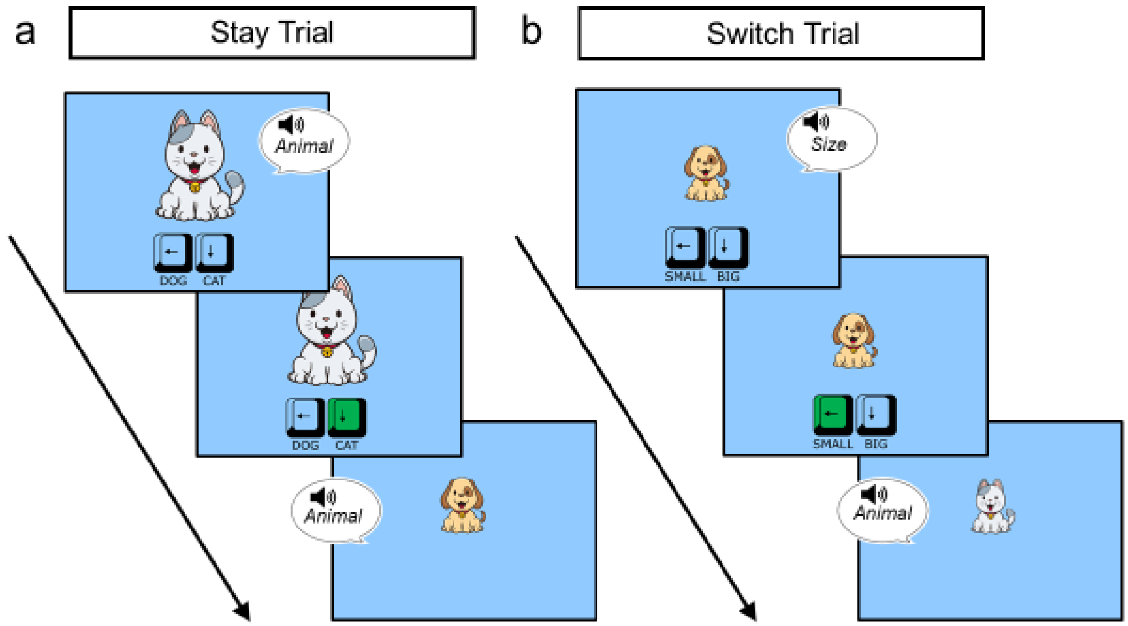


Figure S-6. Cognitive flexibility task where participants had to indicate either the type or size of animal presented. Stay trials were preceded (a) by a trial with the same rule. During switch trials (b), the current trial was preceded by a trial in a different dimension.

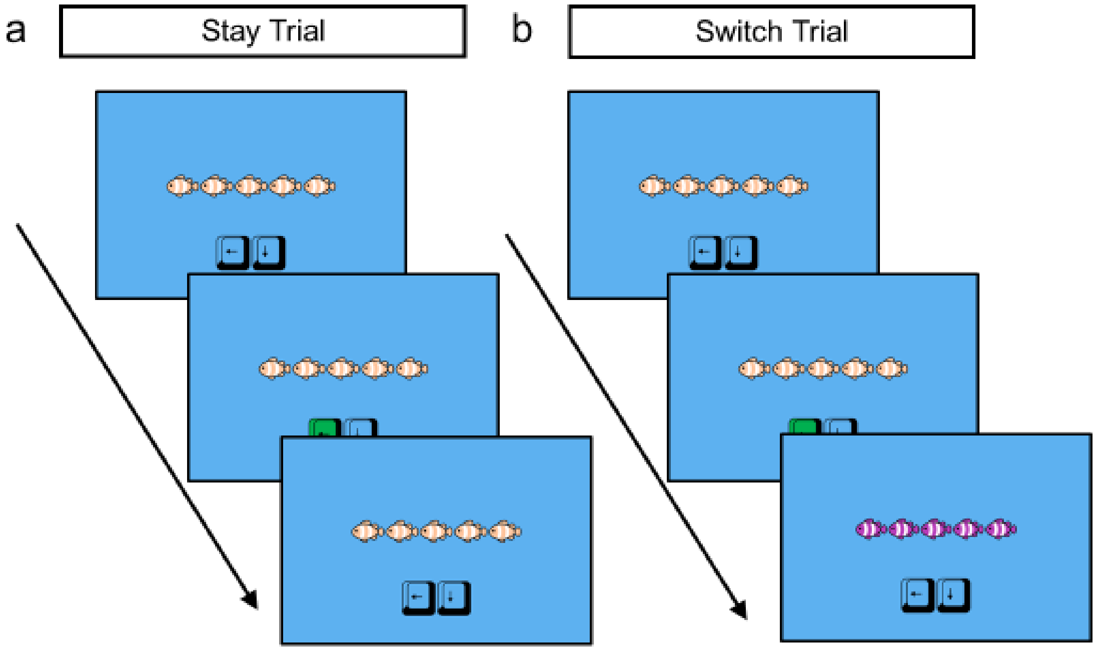


Figure S-7. Flanker shifting task where there were two different sets of rules (i.e. purple/orange). When orange fish were presented, they were instructed to indicate the direction in which the fish swam. When purple fish were presented, they were instructed to indicate the opposite direction in which the fish swam. (a) Stay trials were defined as those where the rule for the previous trial was the same as the current trial. (b) Switch trials were defined as those where a rule change has occurred.

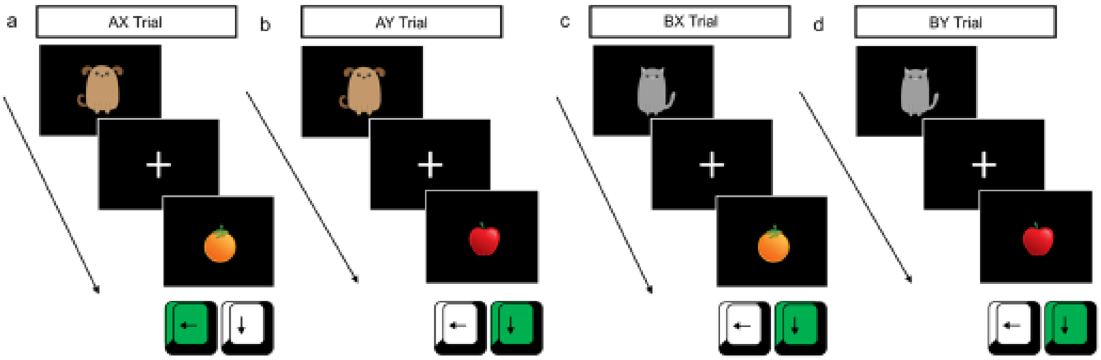


Figure S-8. AX-CPT task indicating proactive and reactive control. During AX trials (a), participants had to respond by pressing the left arrow key. In contrast, during all other trials (b-d) participants had to respond by pressing the down arrow key.

Validation Checks

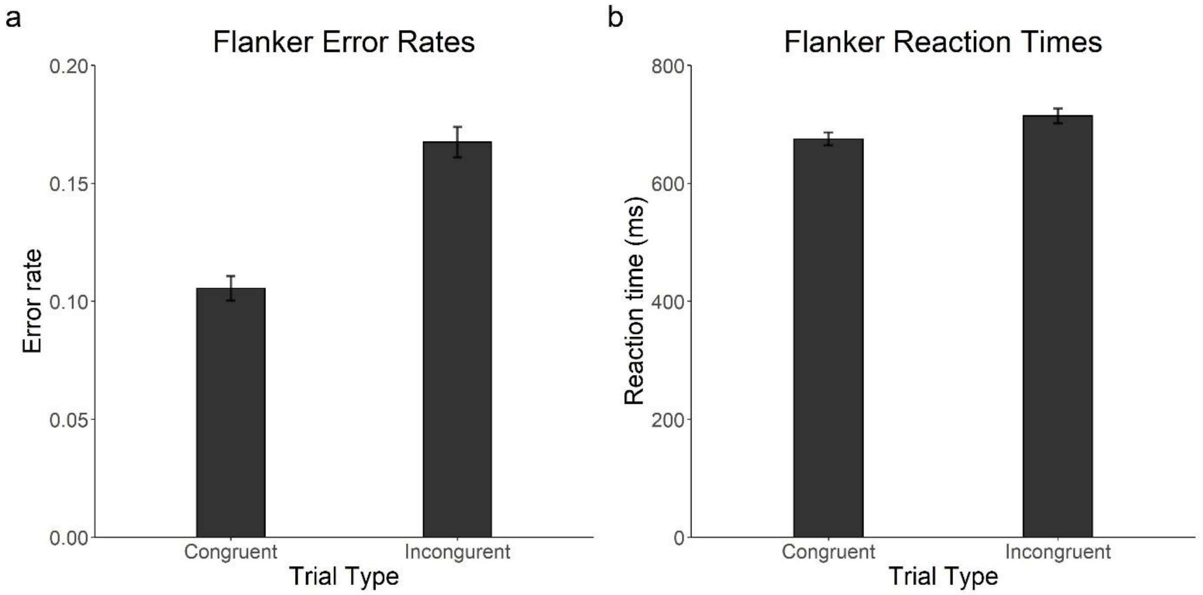


Figure S-9. In the flanker inhibition task, as expected, error rates and reaction times were higher in the incongruent condition as compared to the congruent condition.

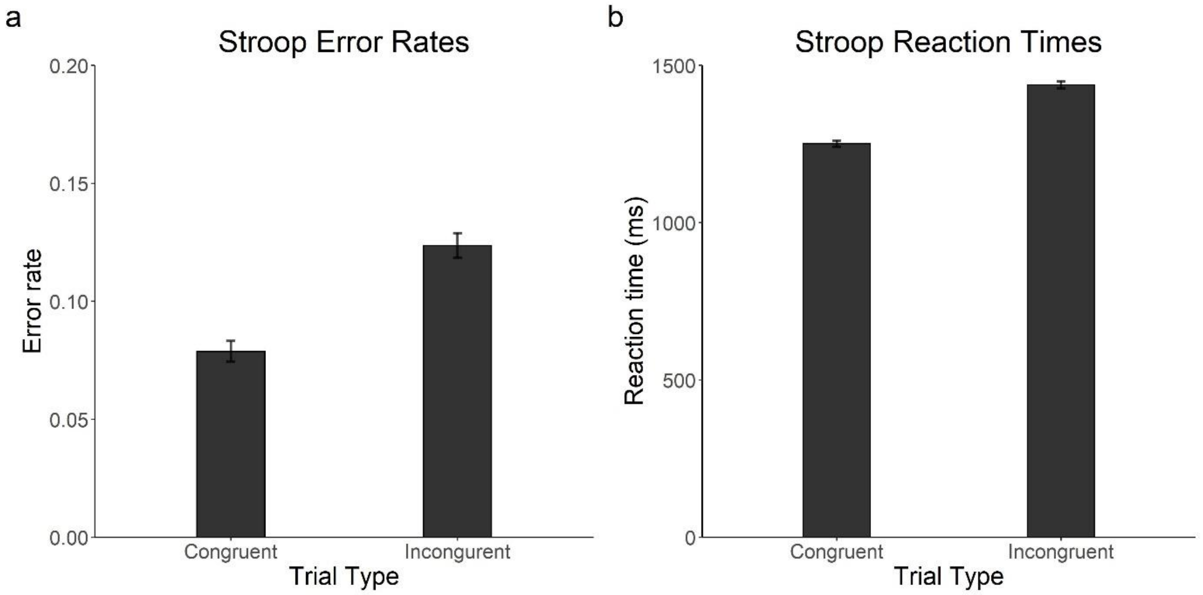


Figure S-10. In the stroop task, as expected, error rates and reaction times were higher in the incongruent condition as compared to the congruent condition.

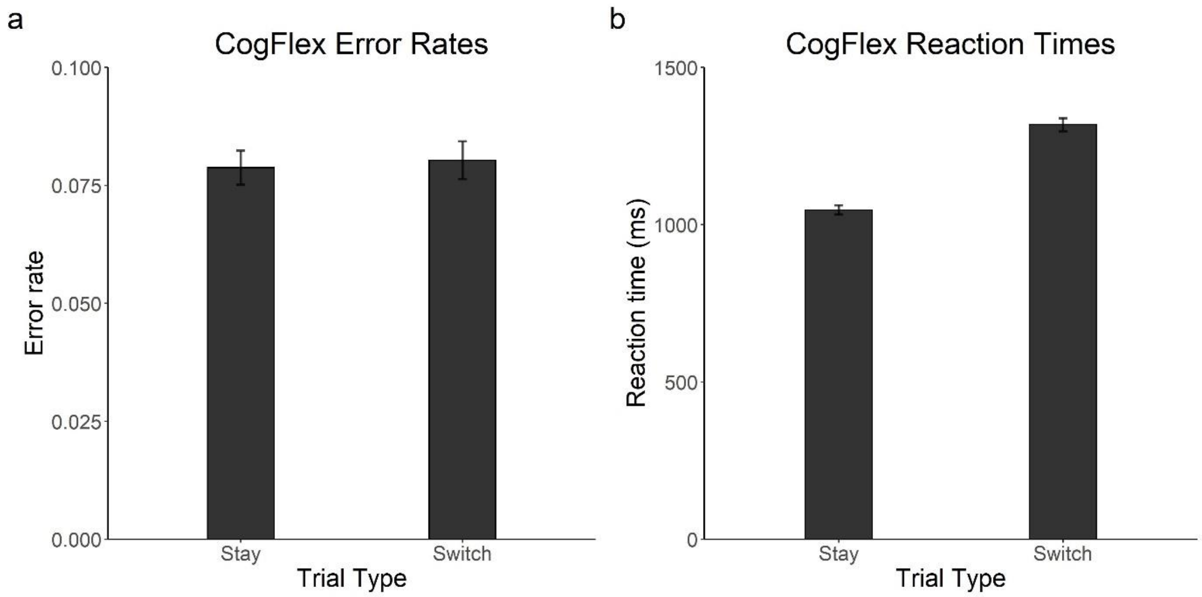


Figure S-11. In the cognitive flexibility task, as expected, reaction times were higher in the switch condition as compared to the stay condition. No differences in error rates were observed between conditions.

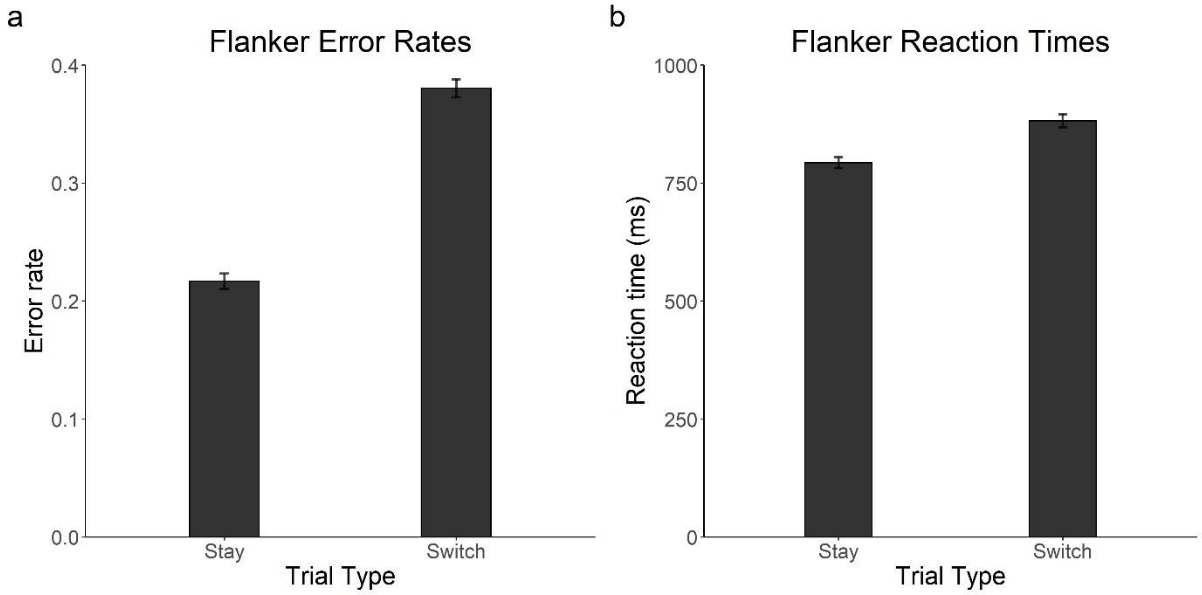


Figure S-12. In the flanker shifting task, as expected, error rates and reaction times were higher in the switch condition as compared to the stay condition.

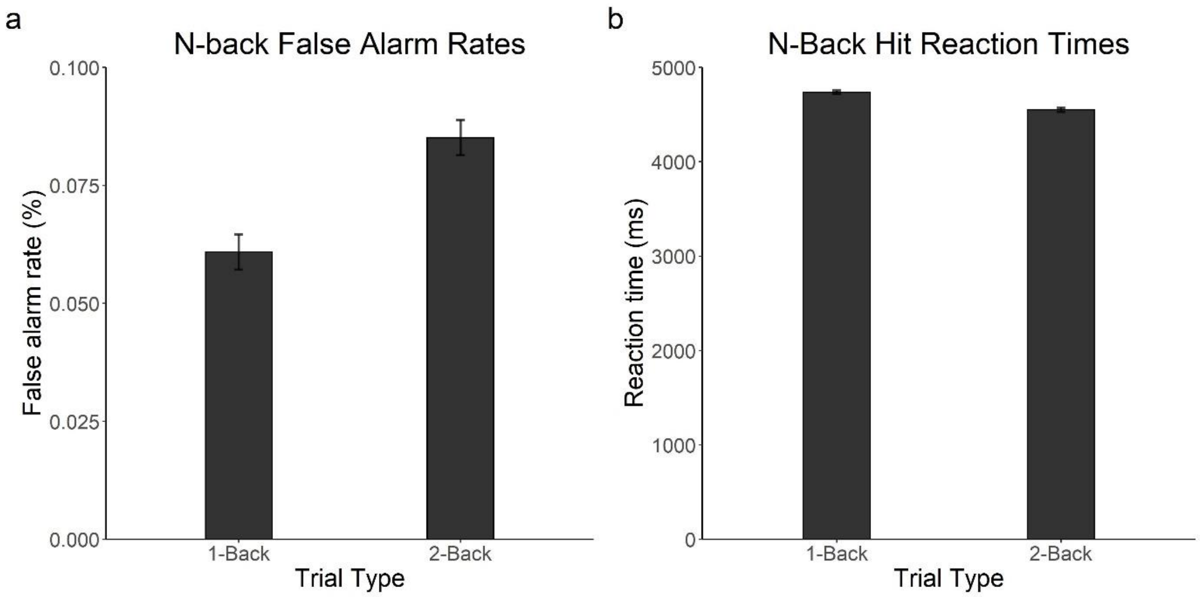


Figure S-13. In the n-back tasks, as expected, error rates were higher in the 2-back task than the 1-back task. No differences in reaction times were observed between tasks.

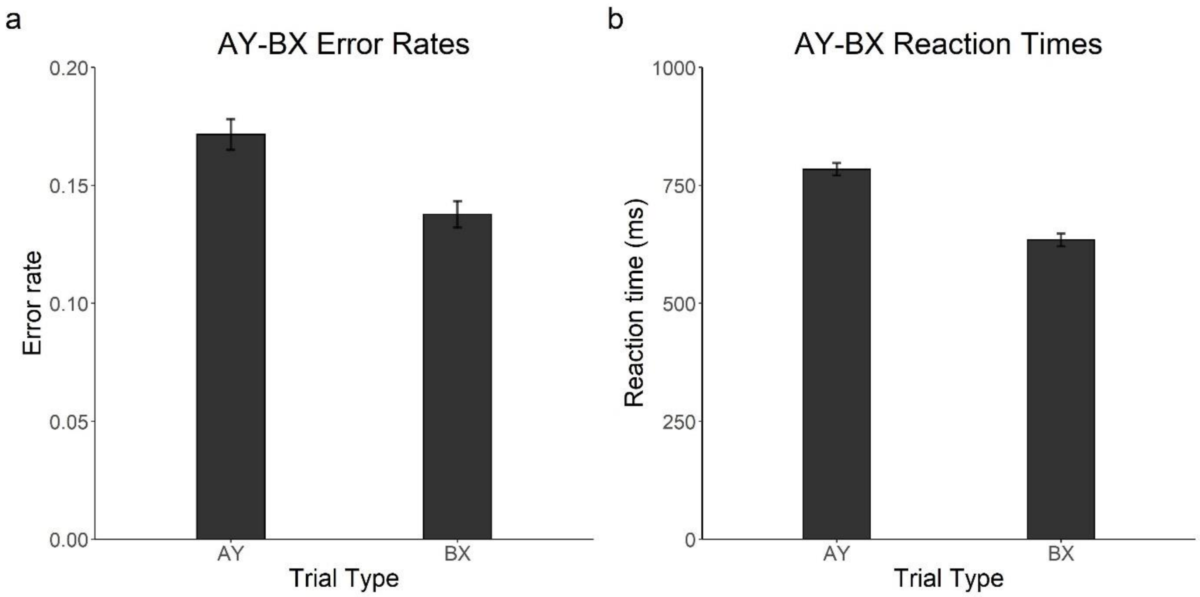


Figure S-14. In AX-CPT task, as expected, error rates and reaction times were higher in the AY condition as compared to the BX condition.

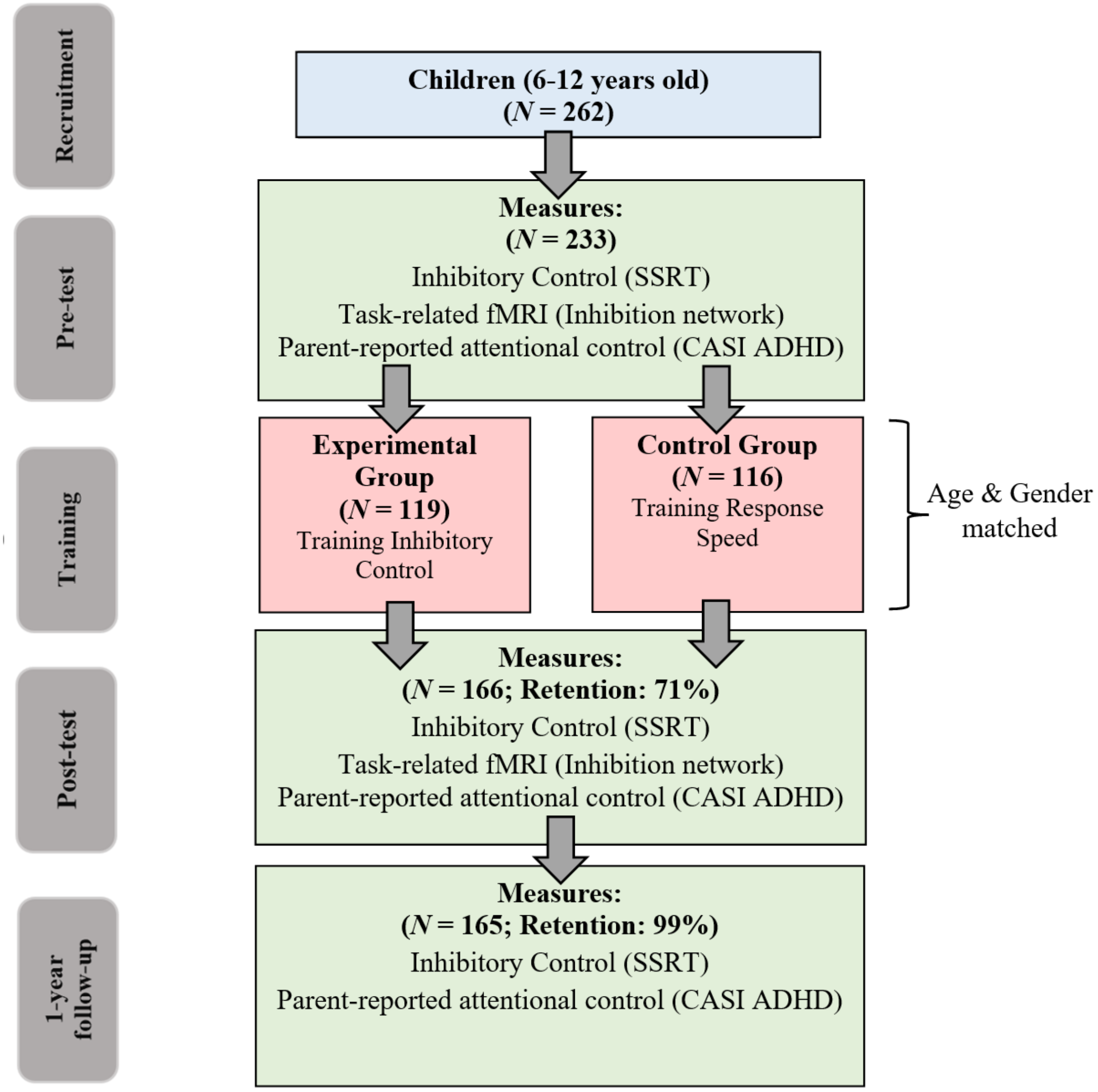


Figure S-15. Study design. Training design and pre-post as well as 1-year follow-up measurements.

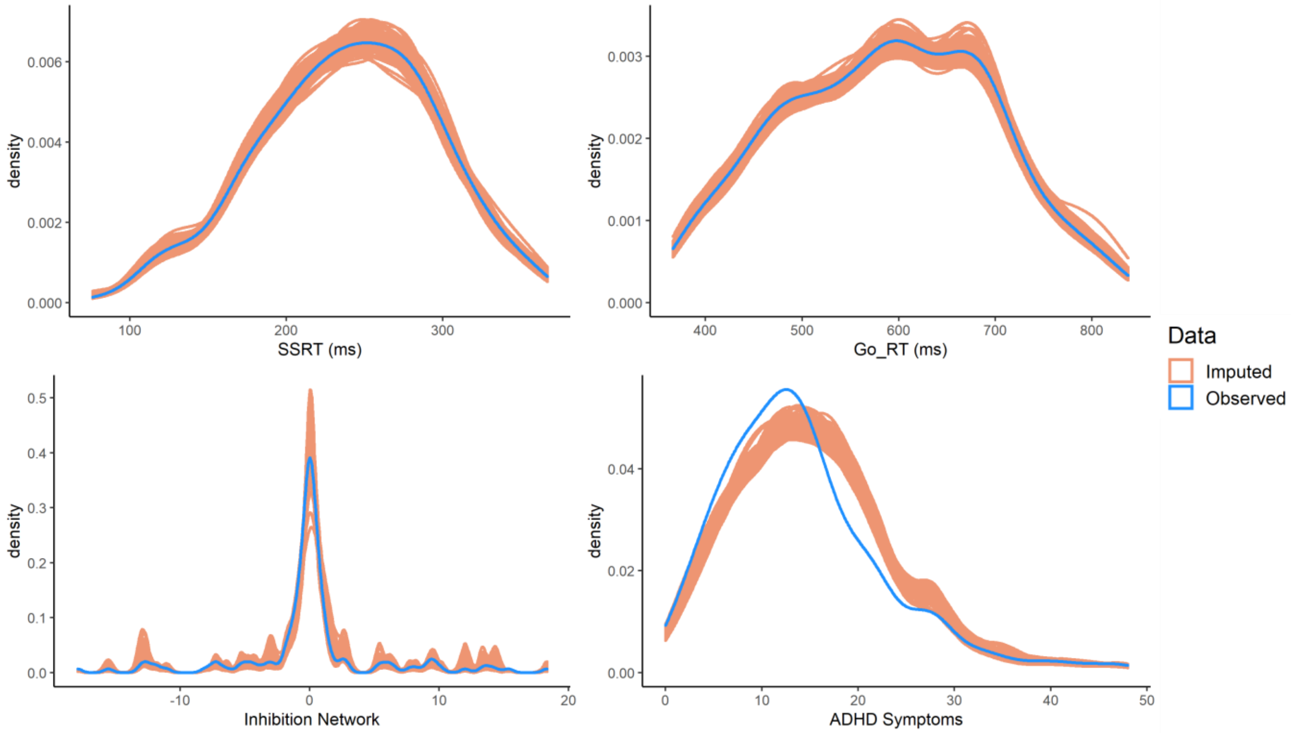


Figure S-16. Imputation of data. Distributions of imputed vs observed data have been shown for main measures of interest.

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10. Author Contribution Statement

Data collected for experimental Chapters 2-6 was done with the help of members of the Developmental Change and Plasticity Lab, UCL. Structural MRI data was pre-processed by Claire Smid for Chapter 2. Functional MRI data was pre-processed with the help and guidance of Dr Roser Cañigueral and Dr Vanessa Puetz for Chapter 5.

11. Publications

Below is list of published and unpublished works during the PhD:

**Ganesan, K., & Steinbeis, N. (2022). Development and plasticity of executive functions: A value-based account. Current opinion in psychology, 44, 215–219. https://doi.org/10.1016/j.copsyc.2021.09.012

**Ganesan, K., & Steinbeis, N. (2021). Effort-related decision-making and its underlying processes during childhood. Developmental Psychology, 57(9), 1487–1496. https://doi.org/10.1037/dev0001228

SUBMITTED/IN PREPARATION

**Ganesan, K., Cañigueral, R., Thompson, A., Smid, C., Puetz, V., Kievit, R. A., & Steinbeis, N. (submitted) Training cognitive control in middle childhood impacts ADHD symptoms. preprint: https://psyarxiv.com/spzjn

**Ganesan, K., Smid, C., Cañigueral, R., Thompson, A., & Steinbeis, N. (in prep) Structural correlates of factors of executive functioning during childhood.

**Ganesan, K., Thompson, A., Smid, C., Cañigueral, R., Kievit, R. A., & Steinbeis, N. (in prep) Effects of cognitive control training on executive function factors.

**Ganesan, K., Smid, C., Thompson, A., Buchberger, E. S., Spowage, J., Iqbal, S., Phillips, H., & Steinbeis, N. (preprint). Not context monitoring but inhibition plays a privileged role in childhood cognitive control. https://doi.org/10.31234/osf.io/kuebx

Cañigueral, R., Ganesan, K., Smid, C. R., Thompson, A., Dosenbach, N. U. F., & Steinbeis, N. (submitted). Adaptiveness of fluctuations in intra-individual variability of performance is process-dependent in middle childhood. Journal of Experimental Psychology. preprint: https://doi.org/10.31234/osf.io/y7c5d