

RELATING UNPREDICTABLE EXPECTANCIES IN WORKING MEMORY TO COMPLEX  
TASKS: NETWORK CONNECTIVITY AND TRAINING-RELATED TRANSFER

by

Margaret A. O'Connell



APPROVED BY SUPERVISORY COMMITTEE:

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Chandramallika Basak, Chair

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Daniel Krawczyk

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Denise C. Park

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Bart Rypma

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This document is dedicated to my family, who have supported me from afar and continue to be my biggest fans. Thank you for the time, words, and constant love for not only the past six years, but the last twenty-nine. To Tommy, who knows when to bring me chocolate and lets me practice presentations, when he has no idea what I am talking about. To my friends within the program, who have kept me sane in the most stressful of times.

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MARGARET A. O'CONNELL, BS, MS

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Margaret A. O'Connell, PhD  
The University of Texas at Dallas, 2018

Supervising Professor: Chandramallika Basak, PhD

Complex tasks involve competing elements, have subtasks and/or varying information loads that involve working memory, include unspecified strategies for task completion, and are required when successfully navigating challenges in everyday life. A strong relationship between working memory and complex tasks has prompted the use of working memory training to improve complex task performance. However, these past interventions have resulted in mixed findings. In the current dissertation we investigate whether these mixed findings are driven by the variability in probe-cue expectancies used in these intervention studies. Therefore, in the two experiments presented in this dissertation, we investigated the relationship between complex tasks and the probe-cue expectancies in working memory. In the first experiment, a randomized control trial, we compared potential improvements from two types of working memory updating training, one with predictable probe-cue expectancies, and other with unpredictable probe-cue expectancies, against an active control group. All three groups were assessed on complex task performance before and after 10 hr (across 5 sessions) of either training or completion of 10 hr of word puzzles (active control group). The two working memory training groups showed significantly

more improvements in a complex task outcome than the control group. The complex task outcome included standardized tasks of episodic memory, reasoning, task switching, and inhibition. When these cognitive constructs were dichotomized, we found that the two working memory training groups improved significantly more than the control group in both the inhibition construct and the episodic memory construct. Using performance in the trained tasks, we investigated the effect of individual differences on transfer, finding that initially high performers and better learners in the unpredictable expectancies group had significant improvements in the complex task, inhibition, and episodic memory measures, compared to the control. However, only low initial performers in the unpredictable expectancies group, and not the predictable expectancies group, resulted in these same improvements for the inhibition measure, compared to the control group. In the second experiment, we investigated how skill learning of novel complex tasks are related to task-related functional connectivity of two attentional networks (cingulo-opercular, CO; fronto-parietal, FP). CO and FP seed-to-voxel connectivity was investigated during three tasks of increasing cognitive control demands; two of which included unpredictable probe-cue expectancies. Complex task learning was related to within-network connectivity for these attentional networks (e.g., CO to CO), and to between-network connectivity for the attentional networks (e.g., FP to CO) and to the default mode (DM) network (e.g., FP to DM) during the tasks with unpredictable probe-cue expectancies. These two studies indicate that better learners in complex tasks utilize within- and between-network connectivity of the neural networks that underlie working memory during tasks with unpredictable expectancies. Furthermore, training in working memory, particularly with unpredictable probe expectancies, will transfer to complex tasks. These findings suggest why

working memory and complex tasks are related (Experiment 2) and how we can strengthen this relationship (Experiment 1).

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## CHAPTER 1

### GENERAL INTRODUCTION

*Attention... is the taking possession by the mind, in clear and vivid form, of one out of what seem several simultaneously possible objects or trains of thought, localization, concentration of consciousness are of its essence. It implies withdrawal from some things in order to deal effectively with others...*

-James, 1890

*The ways creative work gets done are always unpredictable, demanding room to roam, refusing schedules and systems. They cannot be reduced to replicable formulas.*

-Rebecca Solnit

#### 1.1. Rationale

Efficiently executing a new complex task requires adequate working memory abilities, such that individuals with high working memory capacity usually outperform individuals with low working memory capacity in complex task performances. Such complex tasks include reasoning (Kyllonen & Christal, 1990), reading comprehension (Swanson, Xinhua Zheng, & Jerman, 2009), and mathematics (Swanson & Jerman, 2006). Therefore, it is important that we develop a better framework of the relationship between working memory and complex tasks. In the current dissertation we intended to understand *how* working memory and complex tasks are related using a behavioral approach, and *why* they are related using neuroimaging techniques.

Working memory is defined as the ability to actively maintain and store a select capacity of information over an appropriate amount of time while doing a complex task by resisting interference and by updating maintained information (Miyake & Shah, 1999). Working memory capacity is limited, therefore, the items that are needed must be maintained in a temporary buffer or the active store, unless they require immediate operation, such as updating. If so, these items are brought into a capacity limited focus of attention where the item is compared and updated

(Basak & Zelinski, 2012). Training individuals on working memory has been found to not only improve other tasks of working memory, indexed by both neural and cognitive plasticity, but also has found to improve performance on novel complex tasks (e.g., reasoning tasks, Jaeggi, Buschkuhl, Jonides, & Perrig, 2008) across the adult lifespan (for comprehensive meta-analytic reviews, see Au et al., 2015; Karbach & Kray, 2009; Karbach & Verhaeghen, 2014; Klingberg, 2010). The primary goal of any cognitive intervention, we believe, involves training on a cognitive task that promotes transfer to untrained domains of cognition, particularly complex tasks. Although working memory training has been extensively used as a cognitive training tool, many different tasks have been used, particularly the N-back task (Au et al., 2015a; Redick & Lindsey, 2013). The N-back task requires participants to predictably compare the current stimulus to the stimulus presented N positions back in the list. For example, Figure 1.1 is an exemplar of a modified 2-back, in which participants must compare the current digit to the one presented 2 positions back. In this instance, the addition (viz. modified N-back) of color acts as a cue to the comparative trial. Evidence of far transfer from N-back training is small to moderate at best (e.g., Au et al., 2015, reasoning Hedge's  $g = .24$ ,  $SE = .07$ ; Melby-Lervåg & Hulme, 2012, reasoning *Cohen's d* = .19, word decoding *Cohen's d* = .13, arithmetic *Cohen's d* = .07; Redick et al., 2013, verbal reasoning  $p = .68$ , spatial reasoning  $p = .54$ ). It is possible, though, that there may be a better working memory training strategy than training on the N-back task (or even the dual N-Back task) for improving transfer to untrained domains of cognition. For instance, probe-cue expectancies may unintentionally affect which domain of cognition we find transfer to.

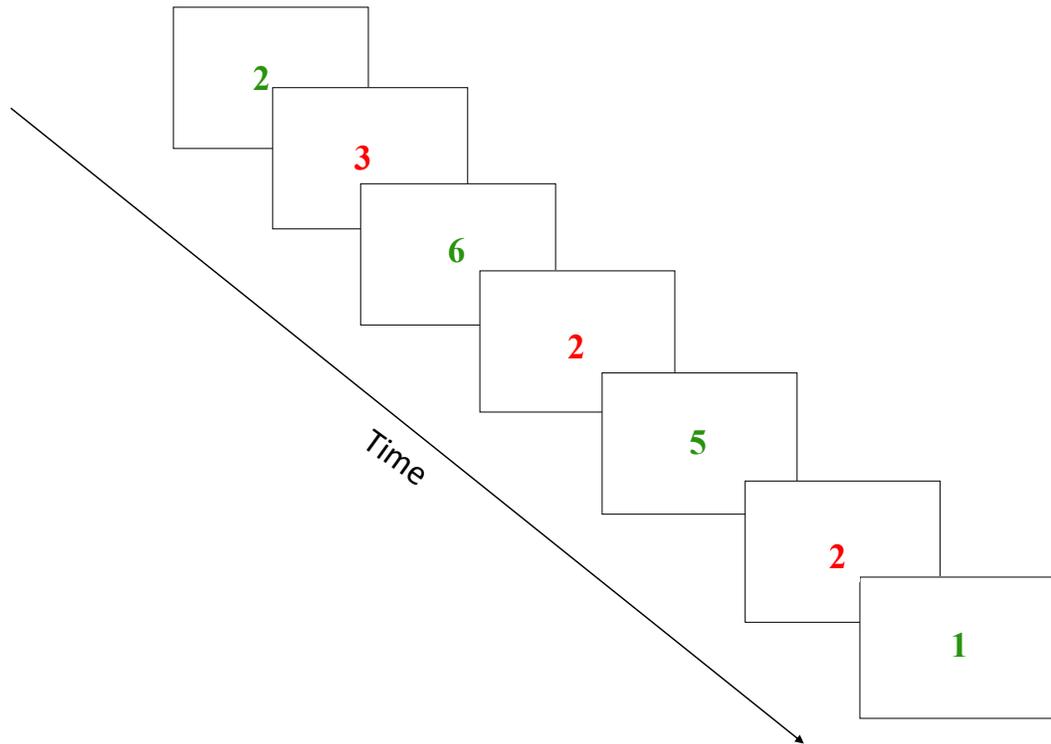


Figure 1.1. Modified 2-back task. Participants are required to compare the current stimulus to the one presented 2 (or N) positions back in the list. For instance, the green “1” would be compared to the green “5” and identified as *different*.

Probe presentation can be either fixed (predictable) or random (unpredictable) in their order. The N-back task (and even the dual N-Back task) has predictable probe expectancies, with each probe requiring retrieval of the  $N^{\text{th}}$  previous item in the list, where N is fixed within a task block. This allows for preparedness in retrieving an item into the focus of attention for task completion. In contrast, tasks where probe expectancies are unpredictable (or random) do not allow for prepared attention (Basak & Zelinski, 2012), and result in greater cognitive control requirements (Basak & Verhaeghen, 2011b). Literature in working memory training primarily focuses on these fixed expectancies. However, transfer from these predictable trainings are highly variable, and often limited to tasks of working memory (for review see: Melby-Lervåg &

Hulme, 2012; Shipstead, Redick, & Engle, 2012). One study has contrasted unpredictable expectancies with predictable expectancies in working memory training to illustrate transfer to tasks of untrained cognition in older adults (Basak & O'Connell, 2016), but replication of these effects are necessary to better understand the benefits of unpredictable probe-cue expectancy training in younger adults.

In the current dissertation we hypothesized that random expectancies require a greater degree of cognitive control components and engender greater demands on long-term memory via the salient cues needed to retrieve a probe from the active store (or temporary buffer) in working memory to the focus of attention. In contrast, for fixed expectancies, preplanned attention for upcoming stimuli relies on continually maintained items in the active store, thus requiring maintenance and attentional focus. This suggests that training in a task with predictable expectancies could be limited in transfer to other working memory tasks, whereas training in a task with unpredictable expectancies could transfer to tasks of long-term memory and reasoning as well (Basak & O'Connell, 2016; Basak & Zelinski, 2012). Evidence supporting the hypothesis that unpredictable probe-cue expectancies will transfer to cognitive constructs that rely on cognitive control can further suggest that such expectancies are more related to complex tasks than predictable probe-cue expectancies.

Another strategy to engender robust, far transfer would be to develop a training task that promotes participant's interest and motivation. Using games as tools for cognitive training is of growing interest in the academic field (Simons et al., 2016). The theory underlying gamified versions of experimental paradigms suggests that combining an immersive and stimulating environment with the components of typical cognitive tasks could translate into elevated, and

maybe broader, transfer effects. Commercially developed “brain games” have heterogeneous results of transfer and often publicly exaggerate the extent of transfer found (Simons et al., 2016). We believe that this may be due to the cognitive domains that they target – usually short-term memory or processing speed, which rely on cognitive control mechanisms to a lesser degree than working memory tasks. Therefore, gamifying tasks of working memory may induce more robust transfer to complex tasks due to the known relationship between working memory and complex tasks *and* the hypothesized benefits of a stimulating environmental array.

In the current dissertation we investigated the relationship between working memory and complex tasks using two-independent methodological approaches that included stimulating, game-like environments. For the first methodological approach, by developing an engaging intervention study, which only alters the probe-cue expectancies between two working memory training groups, we investigated what aspect of this particular component (probe-cue expectancy) elicits broader transfer, with specific interest in transfer to complex tasks. A novel training, adapted from Basak and O’Connell (2016), was used to investigate whether 10 hr of training in an engaging version of either a *predictable* or *unpredictable* working memory updating task caused different levels of transfer to both working memory tasks and tasks of untrained constructs of cognition. Though this study expanded on previous research on older adults (Basak & O’Connell, 2016), it is different from Basak and O’Connell in the following ways: the current study uses 1) a younger adult cohort, who have more robust attentional control mechanisms, 2) an individualized adaptive and engaging version of the previously used working memory updating task, and 3) trains individuals on a much larger memory load of continually updated items (i.e., N). Furthermore, the current study included an additional group, the *active control*

group, and implemented a construct-based approach to investigate cognitive transfer by using multiple measures of the same cognitive domain. This behavioral intervention targeted *how* predictability of probe-cue expectancies during working memory training is related to improvements in complex tasks.

The second methodological approach used seed-to-voxel connectivity to investigate how learning of a complex task related to the neural correlates of a working memory task with unpredictable probe-cue expectancies. This experiment investigated whether learning of games, theorized to require cognitive control components, related to functional brain networks, which underlie unpredictable working memory updating. Targeting how learning in ecologically realistic games related to functional connectivity during tasks with unpredictable probe-cue expectancies, similar to that proposed in the first experiment, highlights *why* there is a relationship between unpredictable probe expectancy in working memory and everyday complex skills.

In sum, these two studies investigated *how* and *why* unpredictable expectancies in working memory tasks relate to novel complex tasks by using both behavioral interventions and neural correlates to learning.

## 1.2. Working Memory

Working memory requires maintenance of a select capacity of information while doing a complex task by resisting interference and updating the information maintained (Miyake & Shah, 1999). The theoretical construct of working memory directly relies upon the additive process of cognitive control operations (Burgess et al., 2006). These operations can be functionally investigated independently or in combination for more complex constructs, like working

memory. Historically there have been different models of working memory that focus on the modality of information held in working memory or the capacity limitations of operationally supported partitions in working memory.

### 1.2.1. Multi-Component Model of Working Memory

The multi-component model, proposed and updated by Baddeley and Hitch (Baddeley, 2001; Baddeley, 1986; Baddeley & Hitch, 1974) suggests that working memory is fractionalized into modality specific buffers. For instance, the phonological loop holds sequences of verbal-based items and assumes that verbal rehearsal allows for the temporary storage of this information. Support for the phonological loop was provided by evidence from studies using phonological similarity and articulatory suppression (Murray, 1968). The visuo-spatial sketchpad, in contrast, is a buffer that consists of a passive store of visual information and an inner scribe for active rehearsal of spatial information. Modality separate buffers were supported by divided attention tasks that either required participants to complete tasks of the same modality (e.g., entirely verbal) or one of each modality (e.g., verbal and visuo-spatial). Results indicated poorer performance when both tasks were of the same modality but not when tasks were one of each modality. The central executive is an element suggested to be the attentionally-driven proponent of the model, which focuses attention to the correct slave system for a particular modality (or buffer). Further additions on the original model have included both an episodic buffer, to act as a backup store for additional modalities, and links from the original buffers to long-term memory (Baddeley, 1986; Baddeley & Hitch, 1974; Baddeley, 2001; Baddeley, 2000). Baddeley and Hitch hypothesized that frontal brain activation during a working memory task is neural evidence for the central executive, whereas activation in posterior regions or regions

within the memory system, is neural evidence for the different buffers, with regional differences representing the modality-specific buffers. Although many still recognize the multi-component model as the leading model of working memory, there are many flaws that have been accounted for in another working memory model: the hierarchical models of working memory. Particularly, the hierarchical models of working memory first developed a proposed relationship between long-term memory and working memory (Cowan, 2001). Furthermore, in contrast to the multi-component model, the relationship between working memory and long-term memory in the hierarchical models of working memory does not limit the number of possible modalities able to be manipulated in working memory. The execution of complex tasks requires retrieval of past experiences from long-term memory, whereas the learning of complex tasks requiring encoding of new experiences into long-term memory, both across a wide variety of modalities. Therefore, this relationship between working memory and long-term memory is critical in understanding of how working memory influences complex task learning or performance.

### 1.2.2. Hierarchical Models of Working Memory

The hierarchical models of working memory focus less on the modality of information held in working memory, and rather on the cognitive control operations that are utilized during working memory processes. Specifically, while working memory updating is defined as the process of maintaining information while concurrently manipulating and updating previously presented information, it is also considered to be capacity limited. Thus, there is an emphasis on refreshing a subset of information when updating is required, which is driven by the capacity limits of working memory. The current hierarchical models of working memory propose distinct levels of activation: the *focus of attention* and *outer store* (Basak & Verhaeghen, 2011b; Cowan

& Cowan, 2005; McElree, 2001; Oberauer, 2002). Focusing of attention requires ignoring distractors (Basak & Verhaeghen, 2011a) and is believed to be subserved by fronto-parietal regions (Nee & Jonides, 2011; Öztekin, Davachi, & McElree, 2010). In contrast, the outer store is argued to hold information in an activated state of long-term memory (LTM) and is believed to be subserved by the medial temporal lobe (Nee & Jonides, 2011; Öztekin et al., 2010).

Cowan's original hierarchical model was a nod to Donald Hebb (1949), who hypothesized that working memory is caused by an assembly of active, reverberating neural circuits that carry the focal point of attention to specific regions of the brain. Translating this cellular hypothesis to theoretical, Cowan (2001) pioneered a multi-tier model of working memory, differentiating the levels of activation by the mechanistic processes driving them: attentional control and LTM, which subsequently incorporated the cellular deviation hypothesized by Hebb (1949). Cowan's model differs from later hierarchical models of working memory (e.g., Concentric model, Oberauer, 2002; Theory of Working Memory Adaptability, Basak & Zelinski, 2012) in the capacity limitations of the focus of attention. Regardless of the differences between the proposed models of working memory, there is a consensus on the apparent interplay between cognitive control operations and LTM. At the core of these hierarchical models of working memory is the focus of attention. Drastic environmental changes or voluntary control over attention drives a particular subset of information to be brought into the focus of attention. This is similar to the Early Selection model proposed by Broadbent (1958), which suggested that only one independent channel of information can be attended at one time, thus switching between channels is necessary for attending to all information in the environment. Therefore, working memory ability is directly related to how well an individual is able to control and focus their

attention to the target information, while suppressing the non-target information (Engle & Kane, 2004). Experimentally, studies have found that the focus of attention differs from the *outer store* in reaction time and retrieval accuracy, which has provided evidence for the immediate accessibility and high availability of items within the focus of attention (Verhaeghen & Basak, 2005). A decline in accuracy for items presented earlier in a list (i.e., the items in the outer store) has been argued to be due to interference, decay, or both, whereas the more recent item(s) (i.e., the focus of attention) have been argued to be impervious to these effects (Basak & Verhaeghen, 2011a; Verhaeghen & Basak, 2005).

Cowan's model (2001) constrains attentional capacity at about 4 items; this differs from other models which identify a limited capacity of only one item (McElree, 2001; Oberauer, 2001; Verhaeghen & Basak, 2005). The difference in focus of attention capacity is suggested to be a direct result of task-related demands, particularly the quantity and difficulty of cognitive control operations (Basak & Verhaeghen, 2011a; Basak & Zelinski, 2012). A task that requires effortful, sequential updating will have a more constrained focus of attention than a task that requires minimal or no updating. For instance, in a task where a participant is able to chunk information, the focus of attention may include more than a single item, however, constant updating would make this strategy difficult (Cowan, 2005). A significant focus switch cost was observed in the response latencies between the information unit currently updated versus the unit updated prior to the current one (Basak & Verhaeghen, 2011b, 2011a; Garavan, 1998; McElree, 2001; Oberauer, 2002; Voigt & Hagendorf, 2002) or between a set-size of 1 item versus 2 or more items (McElree, 2001; Verhaeghen & Basak, 2005). This supports the hypothesis that the focus of attention has a single item capacity. Analogous studies (Basak & Verhaeghen, 2011a;

Oberauer, 2002; Voigt & Hagendorf, 2002) used a count update task, where the count associated with an information unit had to always be updated and the number of information units varied in set-size (1, 2, or more). These studies found substantial focus switch costs when switching between two information units; this cost increased with increases in set-size (Basak & Verhaeghen, 2011a; Oberauer, 2002). Therefore, the number of items outside of the focus of attention adds cognitive demand of first searching for the relevant probed item among the other actively maintained items in the outer store, then forcing the removal of the current item stored in the focus of attention and subsequently replacing it with the updated probe item.

In contrast to items within the focus of attention, the *outer store* is hypothesized to have two tiers: the active store and the passive store. Items within the active store are highly available yet have limited accessibility when compared to the focus of attention (Basak & Verhaeghen, 2011a). These items, which need to be continually updated and manipulated in order to successfully perform the working memory task, are identified and maintained in the active store (Basak & Zelinski, 2012; Oberauer, 2002; Verhaeghen & Basak, 2005). The active store is equivalent, albeit exhaustive to the number of possible modalities, to the phonological loop and visuo-spatial sketchpad of the Baddeley and Hitch multi-component model (Baddeley, 1986; Baddeley & Hitch, 1974; Baddeley, 2000). Furthermore, similarity between features of items within the active store will over-write each other, similar to the phonological similarity phenomenon of the multi-component model. The second tier of the outer store, or the passive store, is equivalent to activated LTM, which holds items that were previously presented but do not need any manipulation or continuous updating; these items are passively held for later comparison (see Theory of Working Memory Adaptability; Basak & Verhaeghen, 2011a; Basak

& Zelinski, 2012). Support of LTM allows essential task information to be held within the outer store (Oberauer & Hein, 2012). Accessibility of items to be retrieved systematically decreases with an increase in the number of items between the focus of attention and probed target (Basak & Verhaeghen, 2011b). Switching attention from the item within the focus of attention to a probed item rearward in the presented list results in an increase in reaction time for a probed item, or a focus switch cost, but only in the active store (Basak & Verhaeghen, 2011b). The Theory of Working Memory Adaptability (ToWMA) argues that information in the active store is susceptible to interference from other actively maintained items and may rely on familiarity-based recognition processes; but the item in the focus of attention can be recalled in its entirety due to high availability and insulation from the items in the active store. The number of items held within the passive store does not influence the reaction time or accuracy of items within the focus of attention or the active store (Basak & Verhaeghen, 2011b; Oberauer, 2002), suggesting that items in the passive store are firewalled from interference from and to these active tiers.

ToWMA also argues that accessibility of items in the active store would vary as a function of switch expectancy. If switching the focus of attention to the relevant information is predictable (or fixed) then the accessibility of information in the active store does not vary with memory load (e.g., the N-back task in Verhaeghen & Basak, 2005). However, if switching from the focus to the targeted information is random or less expectant, then the accessibility slows (i.e., reaction time increases) as the memory load increases (e.g., the random N-Back task in Basak & O'Connell, 2016 and N-count task in Basak & Verhaeghen, 2011b). In sum, the accessibility of information, or the amount of time it takes to bring this information into the

focus of attention, will differ depending on whether focus switch expectancies are predictable or unpredictable.

Extensive practice in a working memory updating task suggests that the focus of attention may be malleable. For instance, practice of 6 to 8 hr in a predictable N-back task resulted in an increased focus of attention capacity to about 4 items in young adults, where N varied from 1 to 5 (Verhaeghen, Cerella, & Basak, 2004). Following practice, reaction time linearly increased at 40 ms/N from N=1 to N=4, suggesting an expanded focus of attention. This linear slope is similar to parallel search found in Sternberg's short-term memory scan tasks (Sternberg, 1966). In contrast, more than 10 hr of practice on an unpredictable N-back task did not change the reaction time dynamics for increasing set-size in switch probes (Oberauer, 2006). Furthermore, the difference in reaction time for an N of 1 and an N of 2 did not dissipate following practice, suggesting that the focus of attention was limited to one item. Therefore, studies indicate that only practice in a predictable memory updating task results in an expansion of focus of attention capacity, which in turn can increase our working memory capacity (Basak & Zelinski, 2012).

Experiment 1 of the current dissertation was designed to assess predictions from the Theory of Working Memory Adaptability regarding the relationship between working memory and complex tasks. For instance, unpredictably switching items from the active store to the focus of attention requires a greater degree of cognitive control, as indicated by slower accessibility (larger focus switch costs) as the memory load increases, in comparison to a relatively constant level of accessibility for items predictably switched from the active store to the focus of attention. Therefore, tasks with unpredictable probe-cue expectancies would be more related to complex tasks and training in a task with unpredictable probe-cue expectancies would result in

greater transfer to complex tasks that rely on cognitive control. In contrast, findings of an expanded focus of attention through training in a predictable working memory updating task may result in increased working memory capacity in other tasks of working memory.

### 1.2.3. Dual-Mechanism Framework of Cognitive Control

In the current dissertation we focused on the temporal dynamics for bringing items within the active store to the focus of attention, particularly the expectancies regarding *when* these items were switched to the focus of attention. The dual-mechanism framework of cognitive control, as proposed by Braver, Gray, and Burgess (2007) and its relation to working memory suggests separable underlying mechanisms for the fixed and random temporal dynamics of probe expectancies. This framework defines attentional control as being proactive or reactive in its ability to adapt to the information being manipulated in working memory. In the current dissertation we strive to draw attention to the similarities between predictable probe-cue expectancies and proactive control, and unpredictable probe-cue expectancies and reactive control. Proactive control prioritizes sustained maintenance of goal relevant information prior to the onset of probed items, thus biasing an anticipatory response for information to be switched into the focus of attention. In contrast, reactive control is a stimulus driven response for switching task relevant information into the focus of attention, specifically in situations marked by high probabilities of interfering information.

Braver (2012) suggested that successful cognition uses both proactive and reactive control, however they are partially-independent of one another and can, therefore, work in parallel. In everyday life one type of control is favored over the other depending on the situation or the individual. For example, if the ‘goal’ is to stop for gas on the way home from work,

keeping this goal actively maintained for a short duration of time will allow for the goal to be met using proactive control, but may deter other behaviors in the mean-time. In contrast, if the goal to get gas is seemingly forgotten but passing a broken-down car is used as a cue, this situational factor can be used to reactivate the original goal using reactive control. Both scenarios have the same end goal, but the control strategy employed depends on the amount of attention free to allocate to the specific goal.

Traditional working memory updating tasks, like the N-back task, require a participant to compare the current probe to a fixed distance rearward in the list. Strategic performers would use proactive control to preemptively bias the correct information to be switched into their focus of attention due to the knowledge of how far back in the list the current stimulus is in reference to. In contrast, in a task where the probe-cue expectancy is random, a participant is unable to prepare for a particular probe-comparison before it is presented.

Braver and colleagues (2007, 2012) postulated that the lateral prefrontal cortex (PFC) is a marker of the specific mechanism of cognitive control by investigating activation during different task events (Miller & Cohen, 2001). For instance, research has indicated that sustained lateral PFC activation is associated to working memory maintenance for anticipatory attention. Therefore, this region is specific to proactive control with sustained activation from the initial presentation of information until the point that the information is used for goal-relevant behavior. In contrast, transient activation of the lateral PFC is tied to reactive control for activation of goal-relevant information following probe presentation.

In addition to the lateral PFC, proactive and reactive control differ in other neurological mechanisms for task completion. For tasks requiring proactive control, the dopaminergic

neurotransmitter system regulates the maintenance of items in the lateral prefrontal cortex by gating what information gets entrance into this maintenance phase, thus allowing only the relevant task information (Braver & Cohen, 2000; Braver & Cohen, 1999). Over the course of the task, the appropriate timing for a phasic burst of dopamine will be learned in order to enable the appropriate signals for updating and maintaining relevant information. The dopaminergic gating allows for the lateral PFC to be sustained rather than transient for proactive control. Without the dopaminergic gating, the lateral PFC is transient for reactive control, but this is evident only when there are enough contextual representations for the relevant stimuli to be reactivated during probe retrieval. Thus, there are other neurological markers of reactive control that directly relate to the contextual information for a particular event or stimuli and resolve potential interference for other reactivated information. Association regions of the medial temporal lobe (MTL) and sensory-specific regions are activated for contextually-bonded information upon retrieval. Moreover, the anterior cingulate cortex (ACC) activates for top-down control for interference resolution (Botvinick, Braver, Barch, Carter, & Cohen, 2001). Therefore, while the phasic burst of dopamine is an indication of proactive control, the activation of the ACC is an indication of reactive control. Specifically, with rapid ACC activation has been found for interference control, to increase response strength, and to control for an incongruent, biased responses.

The parallels between Cowan's proposed neuronal support for the different levels of working memory (2001) and the neuronal evidence from the Dual Mechanisms Framework (Braver et al., 2007) suggests a potential route for targeting specific cognitive mechanisms. For instance, predictable working memory tasks allow for participants to rely upon proactive control,

such that they are then able to maintain information necessary for sustained goal directed attention. A useful strategy for predictable expectancies would be this preplanned maintenance of relevant information, and thus a continual activation of the lateral PFC. In contrast, unpredictable (or random) expectancies rely upon the ability to recall contextual information, and is thus a stimulus driven, reactive control response. If a proactive control strategy is successfully performed, a participant would not have to search through the active store for the relevant information, since it would already be maintained by activation in the lateral PFC. Conversely, if the optimal strategy relies upon reactive control, a participant would have to search through items held in the active store and strengthened by contextual cues from long-term memory (and MTL activation), in order to bring the relevant information into the focus of attention (Braver et al., 2007; Braver, 2012). Experimental design of working memory tasks relying on varying degrees of proactive and reactive control must thus be explicit in the hypothesized mechanisms underlying performance, specifically when the task is implemented in training.

The dual-mechanisms framework of cognitive control suggests that everyday functioning requires both proactive and reactive control for successful cognition (Braver, 2012; Braver et al., 2007), however, in an N-back training, the predictable nature of probe-cue expectancies biases one of the two mechanisms (proactive control). We propose that unpredictable memory updating, which biases reactive control, would transfer to more constructs and complex tasks.

### 1.3. Working Memory Training

Plasticity, which refers to the ability to modify an individual's cognitive or neural mechanisms, has motivated an investigation into the training benefits of working memory. This

is due to the argument that working memory is an underlying “core” component of fluid cognition (Stine-Morrow & Basak, 2011). Working memory has been found to relate to many complex skills, e.g., reasoning (Kyllonen & Christal, 1990), reading (Swanson et al., 2009), and arithmetic (Swanson & Jerman, 2006). Furthermore, working memory seems to underlie many age-related deficits in fluid cognition, including episodic memory (Lewis & Zelinski, 2010; Verhaeghen, Cerella, Bopp, & Basak, 2005; Verhaeghen & Salthouse, 1997). Theoretically this suggests that training in working memory could cause transfer to other cognitive domains. However, using working memory training as a modicum for increasing fluid intelligence has been mixed in results (Jaeggi, Buschkuhl, Jonides, & Perrig, 2008; Rudebeck, Bor, Ormond, O’Reilly, & Lee, 2012; Stephenson & Halpern, 2013) with a systematic quantitative meta-analysis conducted by Au et al. (2015) suggesting a small but significant benefit following an adaptive N-back training (Hedges  $g=.41$ ) in younger adults when compared to a control group (Hedges  $g=.18$ ).

Working memory training in younger adults has mixed evidence of cognitive transfer not only to the specific task that participants are trained in, but also for transfer to other measures of the trained cognitive construct, and transfer to untrained cognitive constructs. Morrison and Chein (2011) suggest two approaches to working memory training: strategy training and core training. These approaches will substantially vary in within-task demands and thus result in different training-related benefits. Strategy training, which requires participants to focus on a specific aspect of the working memory task at hand, yields target and near-transfer related benefits, but lacks transfer to far-domains of cognition (Carretti, Borella, & De Beni, 2007). In contrast, core training, such as Cogmed and COGITO, train participants on working memory

tasks that utilize multiple components of cognitive control at once. Morrison and Chein (2011) suggest broad transfer in core training; this has been supported by many training studies (Basak & O'Connell, 2016; Buschkuehl et al., 2008; Colom et al., 2013; Harrison et al., 2013; Jaeggi et al., 2008; Jaeggi et al., 2010; Karbach & Kray, 2009; Karbach & Verhaeghen, 2014; Klingberg, 2010; Kramer, Larish, & Strayer, 1995; Owen, McMillan, Laird, & Bullmore, 2005; Von Bastian & Oberauer, 2013). However, training-related benefits continue to vary in their extent and domain due to the different task demands targeted within a training study. For instance, while the approach in training may remain consistently core-based or strategy-based, the specific trained task often differs across studies. Task differences not only affect single-study conclusions, but the range of tasks used in different training studies lead to differences in experimenter inclusion criteria for meta-analytic investigation. For example, in a meta-analysis conducted by Melby-Lervåg and Hulme (2012), both strategy and core working memory training studies were included. The extent of significant transfer was limited to tasks of the same cognitive construct (working memory). Transfer to tasks of verbal working memory ( $d=.79$ ), visuo-spatial working memory ( $d=.52$ ), nonverbal ability ( $d=.19$ ), and attentional inhibition ( $d=.30$ ) were significant following working memory training. However, far-transfer to tasks of verbal skill, word decoding, and arithmetic were not significant. Separating the two approaches to working memory training may have resulted in a different finding.

Another meta-analysis, conducted by Karbach and Verhaeghen (2014), investigated the magnitude of transfer in cognitive-control and working memory related training paradigms for studies with both older and younger adults. Although working memory includes many components of cognitive control, Karbach and Verhaeghen distinguished the training groups via

those that trained in working memory function and capacity (working memory) and those that trained in inhibition, dual-task, and interference control (cognitive control). Training groups (both in cognitive control and working memory), active control groups, and passive control groups were compared on performance within trained measures, other measures of the trained cognitive construct, and untrained cognitive constructs. Results indicated that training, regardless of domain, had significantly greater transfer to trained measures (*Cohen's d* = 0.91) in comparison to both passive (*Cohen's d* = 0.13) and active control groups (*Cohen's d* = 0.38). Furthermore, there was a significant difference between active control groups and training groups for measures of the trained cognitive construct, *Cochran's Q<sub>B</sub>* = 26.53, *p* < .001; and passive control groups and training groups for measures of the trained cognitive construct, *Cochran's Q<sub>B</sub>* = 26.11, *p* < .001. The difference between the control groups and training groups in measures of untrained cognitive constructs were less robust but trended in the same direction; *Cochran's Q<sub>B</sub>* = 4.17, *p* < .05 and *Cochran's Q<sub>B</sub>* = .66, *p* = .06, respectively. A random-effects meta-analysis regression was used to investigate the role of duration, type, and age on the specific training-induced transfer. None of these variables had a significant effect on the overall transfer. This suggests that the older and younger adults in training did not differ in the amount of transfer. Furthermore, the amount of time spent in training did not affect the amount of transfer either. Comparisons between cognitive control training and working memory training found marginally significant results for changes in the trained measure and transfer to untrained constructs of cognition, however, these results were in reverse directions. Cognitive control training fostered greater profit within the trained-measures (*Cochran's Q<sub>B</sub>* = 3.16, *p* = .08), whereas working memory training fostered greater profit to measures of untrained cognitive

constructs (*Cochran's*  $Q_B = 3.03, p = .08$ ). While marginally significant, these findings suggest that the specific type of cognitive training will utilize different mechanisms for transfer and, thus, recommends the use of a training paradigm that taps upon aspects of both coordination and updating (i.e., aspects of both cognitive control and working memory).

Therefore, the use of a working memory updating paradigm with either fixed or random probe-cue expectancies was used to directly investigate this suggested pairing of coordination, which is a component of cognitive control, and updating, which is a component of working memory, in cognitive training. A study conducted by Basak and O'Connell (2016), contrasted a predictable updating paradigm to an unpredictable updating paradigm. The updating demands were consistent between the two training groups, but the probe expectancies differed. Results indicated that older adults in unpredictable training performed significantly better in measures of far-transfer after 5 hr of training. These findings suggest that the specific within task elements significantly influenced the mode of transfer, since the two training paradigms only differed in one aspect: probe-cue expectancies. Therefore, with additional studies, it may be possible to prompt specific transfer to complex tasks via the manipulated internal task demands.

#### 1.3.1. Working Memory Training and the Dual-Mechanisms Framework

The majority of working memory updating training studies have employed a predictable N-back task (for review see Melby-Lervåg & Hulme, 2012; Shipstead et al., 2012), where the trained mode of control typically relies primarily upon proactive mechanisms. The neurophysiological marker of proactive control systems proposed by Braver and colleagues (2007) include sustained lateral PFC activation and the dopaminergic pathways. This suggests the possible neural mechanisms for the expansion of the focus of attention during predictable

working memory tasks. For instance, dopaminergic gating is learned for the appropriate phasic bursts in line with updating and maintaining task relevant information. Therefore, over the duration of a predictable expectancies training, timing appropriate updating and maintenance of specific streams of information can be prepared prior to probe presentation. Eventually, this may decrease the time and effort to bring the relevant information into the focus of attention and result in an expanded focus of attention (Verhaeghen et al., 2004). An expanded focus of attention could allow for transfer to other tasks of working memory capacity. In contrast, an unpredictable training, relying primarily upon reactive control, relies upon transient lateral PFC, association regions (MTL), sensory-specific regions, and ACC activation for successful cognition. The necessity for item-specific contextual cues outside of the PFC suggest that training in an unpredictable working memory updating task may transfer to tasks of alternate constructs – specifically tasks of long-term memory and executive functioning.

In sum, in the current dissertation we focused on how probe-cue expectancies (and their underlying neuronal differences) systematically affect transfer to complex tasks, and how the neural correlates during unpredictable switching related to complex skill learning of not just one, but two, ecologically-valid, novel tasks.

## CHAPTER 2

### EXPERIMENT 1

#### 2.1. Rationale

The primary goal of a cognitive training is to produce cognitive and neural plasticity, particularly cognitive transfer to complex tasks. Several studies have found that working memory training is one such tool that engenders these changes (Au et al., 2015; Karbach & Verhaeghen, 2014). However, within-task conditions will prompt different demands on cognitive control components and result in a different pattern and magnitude of transfer. The current study focused on how probe-cue expectancy, while keeping all other within-task components stable, effects behavioral transfer following training.

The most common approach to working memory training has been to use the N-back task (Figure 1.1). In this task, participants are required to compare the current stimulus to the stimulus presented N positions prior in the list. In order to successfully perform the N-back task, information must be continually updated and interference from other stimuli must be resisted. Updating and resisting interference are two critical aspects of working memory (Miyake & Shah, 1999). Meta-analyses conducted on N-back training studies have been mixed in extent of transfer (Au et al., 2015a; Melby-Lervåg & Hulme, 2013; Owen et al., 2005; Redick & Lindsey, 2013). One such meta-analysis found negligible transfer effects to reasoning, reading comprehension, and arithmetic (Melby-Lervåg & Hulme, 2012). It has been proposed that this lack of transfer to complex tasks could be due to the stability of presentation expectancies in the N-back task. For instance, in the 2-back task, a participant is always comparing the current stimulus to the one presented two positions prior in the list, this is the same for any other N in the N-back task. The

current study intended to investigate how the predictability of expectancies affects transfer to complex tasks. The theory regarding *why* predictability of expectancies would affect transfer has previously been supported by studies testing the Theory of Working Memory Adaptability model (ToWMA: Basak & Zelinski, 2012) and the Dual Mechanism Framework of Cognitive Control (Braver & Cohen, 2000; Braver, 2012; Braver et al., 2007). These studies directly influenced the hypotheses of the current study (for more details regarding the Theory of Working Memory Adaptability model, see section 1.2.2. and for more details regarding the Dual Mechanisms Framework of Cognitive Control, see section 1.2.3.).

#### 2.1.1. Focus of Attention Plasticity

The ToWMA model predicts that if switching the relevant information from the outer store into the focus of attention is predictable, then the accessibility of this information held in the outer store does not vary with memory load or increasing N (Basak & Zelinski, 2012). This was supported in a study using a variation of the N-back task (Verhaeghen & Basak, 2005), in which column and color was added as a cue for stimulus comparison. Following an initial jump of 240 ms in reaction time from N=1 to N=2, there was an almost flat change in reaction time from N=2 to N=5. The ToWMA model also predicts that if switching the targeted item from the outer store into the focus of attention is unpredictable, then accessibility slows, and reaction time increases as the memory load increases. This boost in reaction time would be due to the added cognitive control necessary to search and resolve potential interference from the other competing items. This was supported in a study using an N-count task with varying expectancies (Basak & Verhaeghen, 2011b). Following an initial jump from N=1 to N=2, there was an additional increasing slope for N<1. The increase in reaction time with an increase in N had a slope similar

to the Sternberg-like serial search process (Ashby, Tein, & Balakrishnan, 1993; Hockley, 1984). The differences in cognitive control necessary for switching items into the focus of attention for predictable and unpredictable expectancies differentially indicates the ability to rely upon a parallel or serial search process within the outer store and this search process directly influences the second prediction of the ToWMA model.

The ToWMA model predicts that focus of attention capacity may be malleable depending on the predictability of expectancies in the trained task. For instance, the accessibility of information in the outer store does not vary with memory load in working memory updating tasks with predictable expectancies. Studies have found that with enough practice this translates into a seemingly expanded focus of attention (Verhaeghen et al., 2004). In a study conducted by Verhaeghen and colleagues, the difference in reaction time between  $N=1$  and  $N<1$  was 300 ms on the first day of practice in the modified N-back task, which added column and color as cues. After 10 hr of practice this difference decreased to 30 ms (Verhaeghen et al., 2004). This is a similar slope to automatic processing and suggests an expanded focus of attention (Ashby et al., 1993; Hockley, 1984). This is, however, limited to tasks with predictable expectancies. A study conducted by Oberauer (2006) replicated the Verhaeghen et al. (2004) study with the addition of a random probe presentation 50% of the time. Following 10 hr of training in this unpredictable expectancy task, the slope for  $N>1$  remained similar to that found for the serial search process (Oberauer, 2006). This suggests that training in a working memory task with unpredictable expectancies is unable to change focus of attention capacity.

### 2.1.2. Training-related Transfer

The ToWMA model further predicts that the expanded focus of attention found following training in tasks with predictable expectancies could lead to a larger working memory capacity for other, non-N-back working memory tasks (Basak & Zelinski, 2012). Thus, benefits to working memory capacity would generalize following an expansion of the focus of attention. Preliminary results from Basak and O’Connell (in prep), found transfer to the backward span task following 5 hr of training in a working memory updating task with predictable expectancies, in comparison to a control group. The backward span is a measure of working memory capacity (Wechsler, 1939). ToWMA also predicts that training in an unpredictable expectancies task, which has a higher likelihood of interference from previously presented items, would result in transfer to more cognitive constructs due to interference resolution. This prediction is directly supported by the theory underlying the Dual Mechanisms Framework of Cognitive Control proposed by Braver and colleagues (Braver & Cohen, 2000; Braver, 2012; Braver et al., 2007).

### 2.1.3. Dual Mechanisms Framework of Cognitive Control

The deviation between transfer to tasks similar to that which is trained and tasks of other cognitive constructs, depending on the predictability of expectancies within the trained task, is supported by the Dual Mechanisms Framework proposed by Braver, Gray, and Burgess (Braver et al., 2007). The Dual Mechanisms Framework suggests that attentional control for future action either biases proactive or reactive control in its ability to adapt to the information being manipulated. Proactive control prioritizes sustained maintenance of goal relevant information prior to the onset of probed items, biasing an anticipatory response for to-be attended information. It seems that this is primarily what is utilized in performance of working memory

tasks with predictable expectancies. In contrast, reactive control is a stimulus driven response for to-be attended information and is specifically found in situations marked by high probabilities of interfering information. It seems that this is primarily what is utilized in performance of working memory tasks with unpredictable expectancies.

Furthermore, the underlying neural mechanisms proposed by Braver and colleagues directly align with the predicted constructs of transfer proposed by the ToWMA model. For instance, studies have found that sustained lateral prefrontal cortex (PFC) activation is associated to working memory maintenance for anticipatory attention or proactive attention (Braver et al., 2007). In addition to the lateral PFC, the dopaminergic system regulates the maintenance of items in the lateral PFC by gating what information gets entrance into this maintenance phase, thus allowing only the relevant task information. Over the course of the task, the appropriate timing for a phasic burst of dopamine will be learned in order to enable the appropriate signals for updating and maintaining relevant information. This could possibly be the mechanism for an expanded focus of attention with practice in the predictable version of the working memory task. This aligns with the predictions from the ToWMA model.

In contrast, transient activation of the lateral PFC has been found to be tied to the activation of goal-relevant information following probe presentation or reactive control (Braver et al., 2007). This transient activity is only evident when there are enough contextual representations for the relevant stimuli to be reactivated during retrieval. Association regions of the medial temporal lobe (MTL) and sensory-specific regions are activated for this contextually-bonded information. Moreover, the anterior cingulate cortex (ACC) activates for top-down control for interference resolution of the non-relevant information that may be dominant or re-

activated. These diverse regions of activation suggest possible models for transfer, which align with the predictions from the ToWMA model for unpredictable expectancies.

The predictions made by the ToWMA model and supported by the Dual Mechanism Framework was directly tested in a study conducted by Basak and O'Connell (2016). Older adult participants completed 5 hr of training in either a working memory task with predictable or unpredictable expectancies. This task differed from the typical N-back task which predictably switches every trial, so that both the predictable and the unpredictable training groups received switch and non-switch trials. The color that digits were presented in indicated the comparison stimulus. Unlike the N-back task, where comparison was a set distance, this task varied the distance for both the predictable and unpredictable training paradigms due to the equal number of switch and non-switch trials. For instance, in the predictable training, a participant received two stimuli presented in the same color in a row. Thus, the first stimuli in that new color was a switch trial (switched from the previous color) and the next trial was a non-switch trial (the same color as the previous trial), see Figure 2.1. In contrast, for the unpredictable training group the order of colored stimuli was random, see Figure 2.1. Following 5 sessions of training (1hr/session), where set-size was presented in the following order for each session: N1, N2, N3, N4, N4, N3, N2, N1, the unpredictable group resulted in larger gains to a measure of reasoning and a measure of episodic memory than the predictable training group, at moderate effect sizes. These complex tasks suggest that unpredictable expectancies are more related to complex tasks than predictable expectancies.

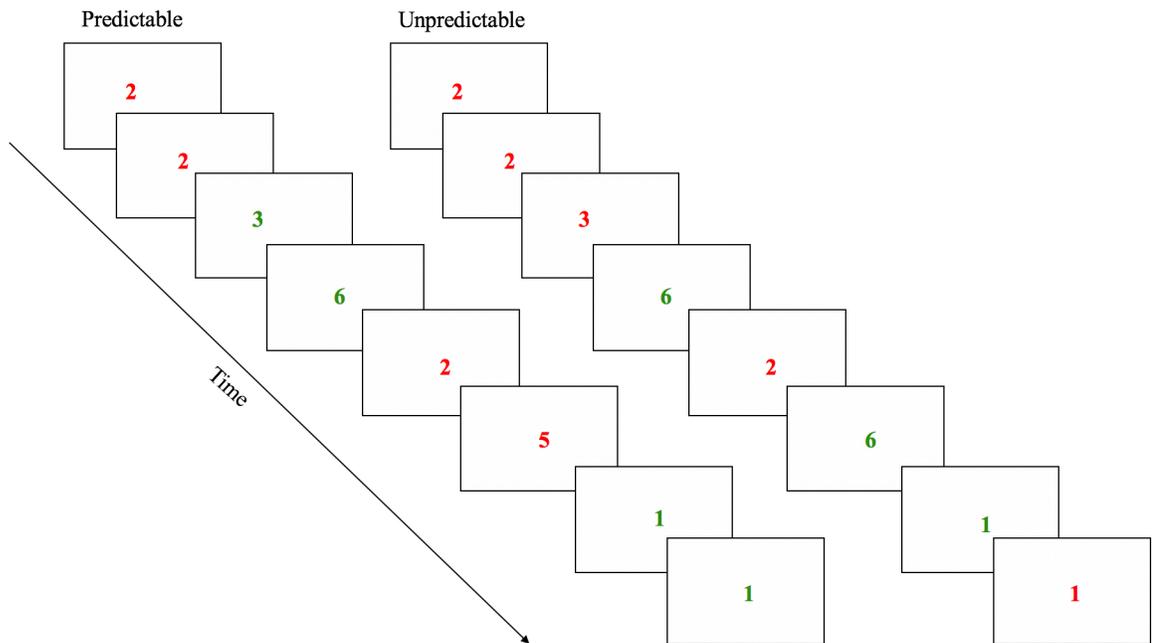


Figure 2.1. Illustration of a 2-match trial run used in Basak and O’Connell (2016): Predictable, where digits were presented in the same color for two consecutive colors before switching to the other color; Unpredictable, where digits were presented in a random color order.

These results suggest that unpredictable probe-cue expectancies target reactive switching and cue-bonding and result in transfer to tasks of untrained cognitive constructs, particularly to complex tasks. Thus, the primary hypothesis of the current study was that training in a working memory task with unpredictable expectancies would bias the reactive control system proposed by Braver and colleagues (2007) and would find transfer to complex tasks, over and beyond that of predictable expectancies training. The secondary hypothesis of the current study was that training in a working memory task with predictable expectancies would expand the focus of attention and bias the proactive control system proposed by Braver and colleagues (2007) and would transfer to working memory capacity tasks. Furthermore, the current study investigated the effects of a more engaging version of the predictable and unpredictable working memory task

used by Basak and O’Connell (2016) in order to investigate whether a longer duration of training (10 hr as opposed to the previously used 5 hr), adaptable difficulty levels, and a game-like platform would prompt targeted and more robust transfer effects. This training was conducted in a younger adult sample, compared to the Basak and O’Connell (2016) paper, which investigated transfer in older adults. It is possible that the current results would differ from the previous findings due to cognitive impairments in an older adult sample, compared to a younger adult sample.

## 2.2. Method

### 2.2.1. Recruitment

All potential participants were recruited from Dallas and its surrounding communities using flyers or an online forum for course research credit from the University of Texas at Dallas. Participants completed a preliminary interview collecting demographic information and study compatibility. All participants were between the ages of 18 and 35, native or fluent English speakers, had normal or corrected 20/30 vision, and did not suffer from color blindness, as assessed using the Ishihara Color Blindness test. Participants were randomly assigned to one of three groups: predictable, unpredictable, and active control.

#### 2.2.1.1. Power Analysis for Estimation of Sample Size

Using G\*power (3.1) to estimate the power to detect differences between the group (3) x time (2) interaction using a medium effect size of Cohen’s  $f=.25$ , which translates to a  $\eta_p^2 = .06$ , we have calculated that a total of 54 participants at the end of training were needed at an alpha of .05. These 54 participants would provide a power of over 90%. Therefore, an initial recruitment

of 73 participants, with a 10% anticipated attrition rate, allowed for random assignment of 23 people to each group.

### 2.2.1.2. Participants

Seventy-three young adults were recruited from the University of Texas at Dallas and the Dallas/Fort Worth Metroplex to participate in this randomized experiment ( $M_{age} = 23.75$ ,  $M_{education} = 15.81$ , 52 females). Four individuals dropped out of the study due to personal reasons; see Table 2.1 for the demographics for each group. There were no differences in age, years of education, and number of females between the three groups.

Table 2.1. Demographic information including mean (SD) of age and education.

	Control Group	Predictable Training	Unpredictable Training	<i>F</i> or $\chi^2$	<i>p</i> -value
<i>N</i>	23	23	23		
<b>Age</b>	24.04(4.97)	24.04(4.62)	23.7(3.57)	0.05	0.95
<b>Education</b>	15.33(2.93)	16.57(3.08)	15.72(2.33)	1.78	0.32
<b>Gender</b>	$N_{Female} = 17$	$N_{Female} = 15$	$N_{Female} = 17$	2.90	0.58

### 2.2.2. Procedure

Participants were randomly assigned to one of three groups. Two of these groups were designed to investigate the relationship between probe-cue predictability, while implementing a brain-game platform based on an adaptation of a traditional working memory task. These two training groups were equivalent to one another with the exception of the temporal dynamics of probe-cue expectancy. Participants were trained on their respective paradigms over five days spanning across two weeks (2 hr/day), amounting to a total of 10 hours of training, such that one week had two training sessions and the second week had three training sessions, or vice versa. Prior to training, all subjects completed an extensive 2 hr cognitive battery of transfer tasks to assess their pre-test performance. Following training, these participants completed this same 2 hr

cognitive battery to assess possible training-related changes in the targeted cognitive constructs.

See Figure 2.2 for the flow of participants through the study.

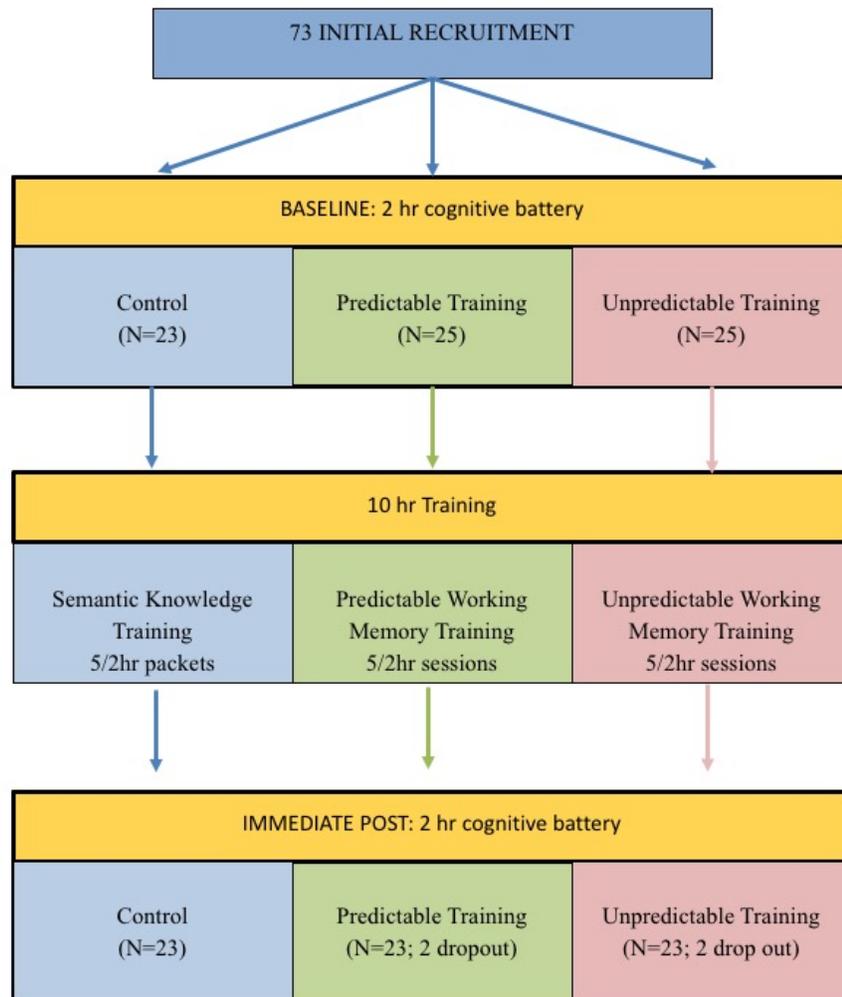


Figure 2.2. Flow of participants through the training study (Experiment 1).

### 2.2.2.1. Apparatus

All computer-based cognitive transfer tasks were programmed in E-prime (Psychology Software Tools, Pittsburgh, PA, USE). The working memory training tasks were programmed in Matlab (MATLAB and Statistics Toolbox Release 2017b, The MathWorks, Inc., Natick,

Massachusetts, United States). The computer-based cognitive tests and training were collected on networked PC computers with 22" Dell P2213 monitors, set to a 60 Hz 1920 x 1080 resolution.

#### 2.2.2.2. Training Procedure

Previous working memory updating paradigms, specifically the modified version of the N-back task, were used to develop the current training paradigms (Basak & Verhaeghen, 2011b; Verhaeghen & Basak, 2005; Verhaeghen et al., 2004), and were programmed by C.B. and H.S. In these tasks, the number of to-be-retained items, or N, varied using different colored digits and were presented in virtual columns - using color and location as retrieval cues. The current training paradigms included bird type and location as similar retrieval cues. Participants assigned to both the predictable and unpredictable training groups played 10 hr of a gamified version of the working memory updating tasks used in Basak and O'Connell (2016). In the training tasks, participants were initially presented with a single tree in the middle of the forest (screen) and had to indicate whether the current bird on the tree was the same ('p' key) or different ('q' key) than the one that was previously presented on that tree. This is equivalent to a 1-back, in which a participant must compare the current number with the one presented directly before. When the previous bird was the same as the current bird, or a non-update trial, stimuli position was shifted on the tree to indicate that the same bird was presented on the same tree in subsequent trials.

Participants keyed 40 trials in each block. Manipulation of training adaptability and challenge across the 10 hr of training increased by block and day of training. For instance, if a participant surpassed eight trees (N=8) on particular training day, they advanced to the next difficulty level the following training day, with a possible three levels of difficulty. For a

difficulty level of 1, a participant was required to surpass an 85% correct criterion before continuing onto the next level or next N. For a difficulty level of 2, a participant was required to surpass a 90% correct criterion before continuing onto the next level or N. Finally, for a difficulty level of 3, a participant was required to surpass a 95% correct criterion before continuing onto the next level or N. When a participant completed a level at the specified difficulty criterion, another tree was added to the forest. Before each level run of 40 trials, distinct birds were shown sequentially on each tree for subsequent comparison stimuli. The participant was then required to indicate whether the current bird presented on a particular tree was the same ('p' key) or different ('q' key) than the last bird presented on that same tree. Therefore, tree location was used as a cue for retrieval of the to-be-compared stimuli, this is equivalent to the columns used in past studies (Basak & Verhaeghen, 2011b; Verhaeghen & Basak, 2005; Verhaeghen et al., 2004). There was a maximum of 12 trees in these training paradigms.

#### 2.2.2.3. Predictable Training

The primary difference between the two training versions of the tasks was the temporal dynamics of the probe sequence. In the predictable training, the birds were presented on the trees in a clockwise rotation, such that following comparison trials, two birds were sequentially presented on each tree before switching to two birds on the clockwise tree location directly next to the current tree. A 50/50 switch/non-switch ratio in each level was achieved due to this two-item sequential presentation. For example, in an N=3 block, the stimuli were presented on the trees (T) in the following order: T1 (comparison trial), T2 (comparison trial), T3 (comparison trial), T1, T1, T2, T2, T3, T3, T1, T1, T2, T2, T3, T3, etc. Such a sequence allowed for

performance measures in both switch and non-switch trials. A non-switch trial was when a bird was presented on the same tree as the previous bird (e.g., T1, T1); a switch trial was when a bird was presented on a different tree as the previous bird (e.g., T1, T2). A 50/50 update/non-update ratio in each level was also achieved. A non-update trial was when the same bird was presented on a particular tree as the last bird presented on that same tree. An update trial was when a different bird was presented on a particular tree than the previously presented bird on that tree. Thus, the switch dynamics were predictable for that particular block, however, updating demands remain to be unpredictable. Figure 2.3 illustrates a N=3 trial for the predictable training group.

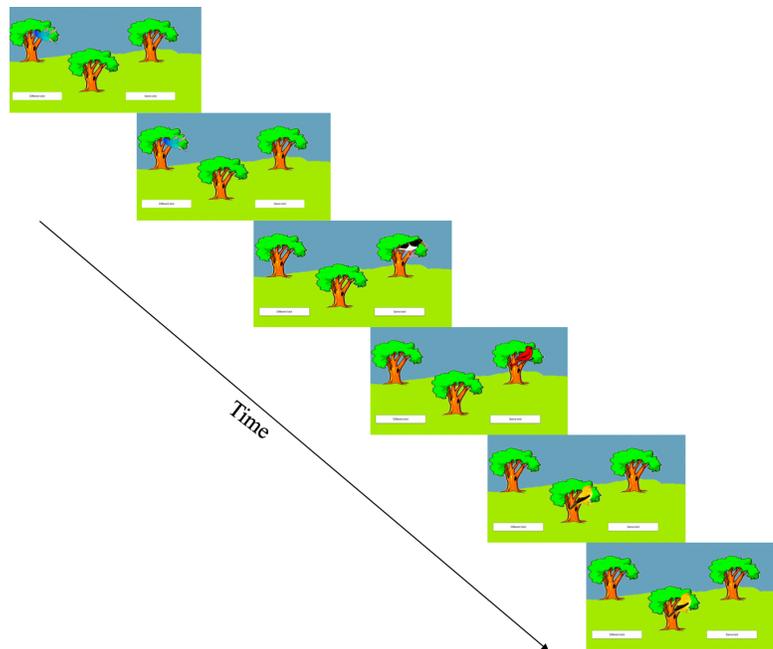


Figure 2.3. Task example for N=3 in the gamified predictable working memory updating task.

#### 2.2.2.4. Unpredictable Training

There were no differences between the two training conditions for the easiest condition, N=1. For N>1, the predictable expectancies training had fixed temporal dynamics, but the

unpredictable training had random temporal dynamics. In unpredictable training, birds were presented on random tree locations following the comparison trials. Similar to the predictable training paradigm, a 50/50 ratio for both switch/non-switch and update/non-update trials was maintained in the unpredictable training paradigm. For example, in an N=3 block, the stimuli could be presented on the trees (T) in the following order: T1 (comparison trial), T2 (comparison trial), T3 (comparison trial), T3, T3, T1, T2, T2, T1, T1, T1, T3, T2. Figure 2.4 illustrates a N=3 trial for the unpredictable training group.

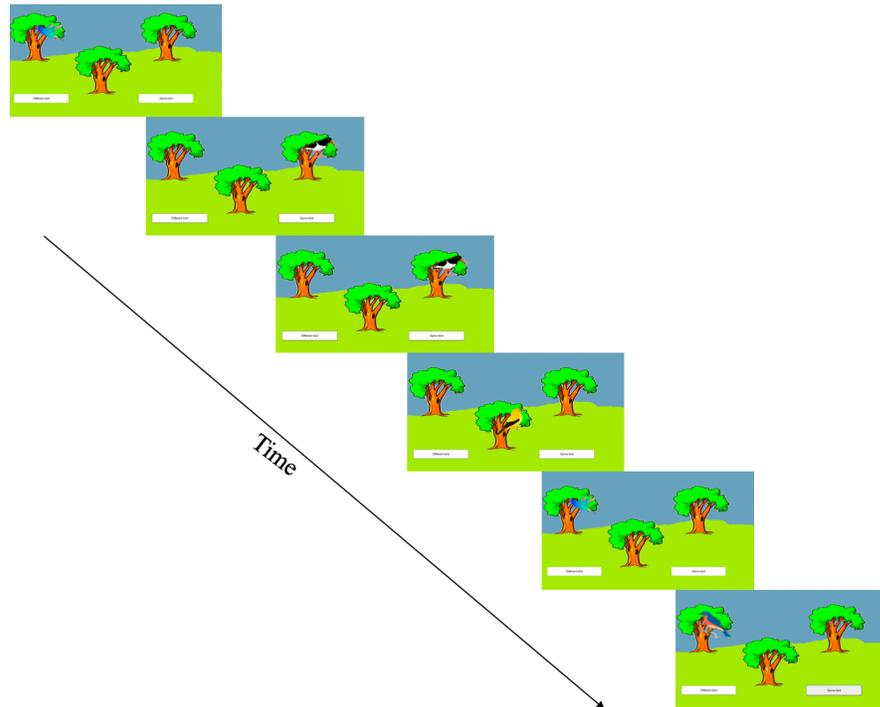


Figure 2.4. Task example for N=3 in the gamified unpredictable working memory updating task.

#### 2.2.2.5. Active Control

An active control group was used in the current study. Participants in the active control group were given verbal word puzzles with time restraints for puzzle completion. Participants were prompted to complete 2 hr of word puzzles per session, with five total sessions. These puzzle tasks varied between crossword, word-search, word-ladder, and word axle puzzles; the puzzle packets increased in difficulty in order to mirror the adaptability manipulation in the training groups.

#### 2.2.3. Neuropsychological Assessment

Participants underwent a pre-test and immediate post-training 2 hr neuropsychological assessment featuring paper and pencil tasks and computerized tasks. Task order was fixed for both testing days.

##### 2.2.3.1. Working Memory Tasks

**Backward Span.** The backward span task was used to measure working memory capacity. During the backward span task participants were required to recall digits in the reverse order that they were auditorily presented in. Two digits were initially presented and immediately recalled; after two fully correct list recollections, the list length incrementally increased by one digit. Participants increased in list length until they failed to correctly recall a list-length twice. The final correct list length was identified as a measure of the participant's working memory capacity. The backward digit span task was taken from the Working Memory Index (WMI) in the Wechsler Adult Intelligence Scale (Wechsler, 1939).

**Computation Span.** The computation span task was used to measure working memory capacity (Conway et al., 2005). In the computation span task, participants saw a simple addition or

subtraction problem (e.g.,  $5 + 3 = 7$ ) and indicated whether the arithmetic problem was correct ('p' key) or wrong ('q' key). Participants then recalled the second number of the equation by entering a 3. There were two additional trials involving only one equation. The number of equations increased by one every three trials, with a total of seven possible equations in a trial. If the order of recalled digits was correct, this was scored as a correct trial. The task terminated if the participant failed to correctly recall the order of two out of the three trials for a particular span. The final span was a measure of the participant's working memory capacity.

**Reading Span.** The reading span task was used to measure working memory capacity (Daneman & Carpenter, 1980). In the reading span task, participants saw a sentence on the screen (e.g., “a part of the body used for seeing things is the eye”) and indicated whether the sentence was true ('p' key) or false ('q' key). Participants then recalled the last word of the sentence by typing in 'eye'. There were two additional trials involving only one sentence. The number of sentences increased by one every three trials, with a total of seven possible sentences in a trial. If the order of recalled words was correct, this was scored as a correct trial. The task terminated if the participant failed to correctly recall the order of two out of the three trials for a particular span. The final span was a measure of the participant's working memory capacity.

**Visual N-Update.** The visual N-update task was most similar to the training paradigm in the current study. Participants were presented with Japanese characters on two different color backgrounds, either yellow or pink. Participants indicated whether the current character was the same ('m' key) or different ('z' key) than the previous Japanese character they had seen on that same color background. Color presentation was unpredictable. Thus, participants needed to actively store and update two streams of information (a yellow stream and a pink stream) at all

times. The first two blocks and last two blocks of the task presented characters on only one color (e.g., N=1). The difference between reaction time for 2-update blocks and reaction time for 1-update blocks, defined as Visual N-Update Global Cost, was used as an indicator of working memory updating.

### 2.2.3.2. Complex Tasks

#### 2.2.3.2.1. Executive Functioning

##### 2.2.3.2.1.1. Task Switching

**CVOE.** The CVOE task switching paradigm required participants to use label cues to determine and switch between specific task rules (Rogers & Monsell, 1995). Participants were presented with letter-number pairs on the screen (e.g., G 11). In the first block of 40 test trials, participants indicated whether the letter was a vowel ('p' key) or consonant ('q' key). In the second block of 40 test trials, participants indicated whether the number was even ('p' key) or odd ('q' key). The final block of 52 test trials swapped labels in the lower right and left corners of the screen every two trials, to indicate whether the participant was attending to the number or the letter. Global switch cost, calculated by subtracting the reaction time of the single task blocks from the dual task blocks, indicated whether maintaining two tasks was more difficult than maintaining one task and was used to measure task switching.

**Task-switching.** This task-switching paradigm (Basak, Boot, Voss, & Kramer, 2008) required participants to use the color background to determine the specific task rules. Participants first completed a block of the blue background task, where participants indicated whether the number was higher ('z' key) or lower ('/' key) than the number five. The number five was never shown. Participants next completed a block of the pink background task, where participants indicated

whether the number was odd ('z' key) or even ('/' key). The final two blocks presented blue and pink background trials intermittently. Stimuli were presented on the screen for 1500 ms. Global switch cost, calculated by subtracting the reaction time of the single task blocks from the dual task blocks, indicated whether maintaining two tasks was more difficult than maintaining one task and was used to measure task switching.

**Trail Making Task: B-A.** Trail Making A required participants to connect circles in numeric order without lifting their writing utensil off the sheet. Trail Making B required participants to switch between connecting circles in numeric and alphabetical order (e.g., 1 to A to 2 to B) without lifting their writing utensil off the sheet. The difference between the total time it took the participant to complete Trail Making B and Trail Making A was used to measure task switching (Corrigan & Hinkeldey, 1987; Gaudino, Geisler, & Squires, 1995; Lezak, 2004).

#### 2.2.3.2.1.2. Inhibition

**Simon.** In the Simon task, participants responded to the direction that a large arrow pointed on the screen (Simon, 1969). In 60 of the trials, the arrow pointed to the left, which participants indicated using the 'q' key. In the other 60 trials, the arrow pointed to the right, which participants indicated using the 'p' key. A third of these arrows were congruent trials, where the arrow appeared on the left side of the screen while pointing left or on the right side of the screen while pointing right. Another third of the arrows were incongruent trials, where the arrow appeared on the left side of the screen while pointing right or on the right side of the screen while pointing left. Additionally, a third of the trials were neutral, where the arrow appeared in the middle of the screen pointing either to the left or to the right. Participants were told to fixate their eyes in the center of the screen between trials. Ability to inhibit incongruent responses was

calculated by subtracting the average reaction time of congruent trials from the average reaction time of incongruent trials. This cost was used to measure inhibition.

**Flanker.** The flanker task required participants to respond to the direction of the middle arrow in an array of five arrows. If the arrow was pointing to the left, the participant pressed the 'z' key; if the arrow was pointing to the right, the participant pressed the '/' key or the backslash key. The middle arrow was either congruent or incongruent in relation to the other four arrows. A congruent trial was when the middle arrow faced the same direction as these other arrows. An incongruent trial was when the middle arrow faced the opposite direction as these other arrows. Ability to inhibit incongruent responses was calculated by subtracting the average reaction time of congruent trials from the average reaction time of incongruent trials. This cost was used to measure inhibition.

#### 2.2.3.2.2. Episodic Memory

**Story Recall.** In story recall participants were read a short story from the MMSE-2: Expanded Version, which has two parallel versions for the different time points of neuropsychological assessment (Folstein, Folstein, & McHugh, 1975). Participants were prompted to recall as many phrases and details from the story as they could remember. Recall was conducted immediately following completion of the story and 30 minutes following immediate recall. The number of correctly recalled details after the 30-minute delay was used to measure episodic memory.

**Associative Memory.** The associative memory task included a learning phase and a testing phase. During the learning phase participants were shown two independent words on the screen. Following presentation of 24 unrelated word pairs on the screen for 3 s, participants entered the testing phase. During the testing phase, participants were presented with 36-word pairs on the

screen and prompted to indicate whether the words were previously learned as a connected pair ('p' key) or the word pair was new ('q' key). Twelve of these 36-word pairs were intact studied pairs, 12 were completely new words, and 12 were rearranged word pairs. The reaction time for word pair correctly identified as either previously learned or new was used to measure episodic memory (Naveh-Benjamin, 2000).

#### 2.2.3.2.3. Reasoning

**Raven's Advanced Progressive Matrices.** In Raven's Advanced Progressive Matrices (RAPM) participants were prompted to find the missing abstract pattern from a 3 x 3 matrix of complex visual designs. The missing pattern was one of eight options provided to the participants below each matrix. The RAPM is a 36-item test that for the purpose of independence of assessments was divided into two 18 question subsets. Version A included the even questions from the first half of the full test and the odd questions from the second half of the test. Version B had the opposite combination of questions. Participants were given 30 minutes to complete as many of the 18 puzzles as possible. This total number of correctly solved puzzles in the RAPM was used to measure abstract reasoning (Raven, 1938).

#### 2.2.3.3. Additional Measures: Processing Speed and Short-term Memory

**Digit Symbol Substitution Task.** The Digit Symbol Substitution Task (DSST) required participants to draw the corresponding symbol to a particular number during a 30s interval. The number of correct symbol-digit pairs was used to measure processing speed (Folstein et al., 1975).

**Forward Span.** The forward span task was used to measure short-term memory capacity. During the forward span task participants were required to recall digits in the same order that

they were auditorily presented in. Four digits were initially presented and immediately recalled; after two fully correct list recollections, the list length incrementally increased by one digit. Participants increased in list length until they failed to correctly recall a list-length twice. The final correct list length was identified as a measure of the participant's short-term memory capacity. The forward digit span task was taken from the Working Memory Index (WMI) in the Wechsler Adult Intelligence Scale (Wechsler, 1939).

#### 2.2.4. Analyses

##### 2.2.4.1. Primary Hypothesis

For the primary analysis, it was hypothesized that the unpredictable training group would result in significantly greater gains to complex tasks following training, compared to both the predictable training group and the control group. Due to limitations in power, the primary outcome measure was a summation across all standardized constructs of complex tasks (including task switching, inhibition, episodic memory, and reasoning). Two analyses were conducted to test this hypothesis. First, a one-way analysis of covariance (ANCOVA) was used to investigate transfer differences between the three groups for this composite complex task score, while controlling for pre-test scores to remove inherent group differences that are external to task-related change. Second, a multivariate analysis of covariance (MANCOVA) was used to further investigate which of these four constructs were significantly different across the three groups. Finally, one-way ANCOVAs were run on the resulting significant constructs from the MANCOVA to identify the direction and magnitude of transfer.

Two additional analyses were conducted to solidify our findings. First, a principal component analysis (PCA) was conducted on the eight measures that make up the complex task

composite. The resulting components and their corresponding ANCOVA analyses are reported in the Appendix. Second, we conducted a JZS Bayes factor ANCOVA on the significant constructs from our primary hypothesis (Rouder, Morey, Speckman, & Province, 2012) to counteract any power-related concerns. These results are reported in the Appendix.

#### 2.2.4.2. Secondary Hypothesis

For the secondary analyses, it was hypothesized that predictable training would result in better performance in working memory capacity following training due to the expansion of the focus of attention. In order to test this hypothesis, separate univariate repeated measures analysis of variance (ANOVA) for the reaction times of  $N = 1, 2, 3, 4$  were conducted for each training group on Day 1 of training and Day 5 of training. Furthermore, paired-samples t-tests were used to investigate whether focus switch cost (i.e.,  $N = 1$  compared to  $N > 1$ ) for the training groups changed after 10 hr of training for each group. These analyses are able to indicate whether there was any evidence of an increased focus of attention for predictable, compared to unpredictable, training.

Finally, a one-way ANCOVA was used to investigate transfer differences between the three groups on the working memory capacity composite score, after controlling for pre-test scores, to remove inherent group differences that are external to task-related change.

#### 2.2.4.3. Exploratory Analyses

##### 2.2.4.3.1. Additional Constructs

Multiple ANCOVAs were run to investigate whether there was transfer differences between the three groups for the additional measures that include working memory updating, short-term memory, and processing speed, after controlling for pre-test.

#### 2.2.4.3.2. Individual Differences

To investigate whether individual differences influenced the extent and construct of transfer, we investigated any group differences in demographic and pre-test measures using multiple one-way ANOVAs, and training-related measures using multiple independent samples t-tests. We extracted the median of the variables that resulted in significant group differences for each independent group and divided our samples into low and high performers for these variables. We conducted ANCOVAs on the significant transfer tasks in previous analyses using a 5-level independent variable of group (low performing predictable expectancies training, high performing predictable expectancies training, low performing unpredictable expectancies training, high performing unpredictable expectancies training, and control group) to predict immediate post-test performance, after controlling for pre-test. The training-related measures included learning rate and initial performance. These measures were calculated by fitting a logarithmic regression equation to a composite of the difficulty level and largest N reached for each training day. If the participant was performing on difficulty level 2, the largest N for that day was coded as  $N + 12$ ; for a difficulty level of 3, the largest N for that day was coded as  $N + 24$ . See Figure 2.5 for a pictorial representation of the coding, the average difficulty level for each training day across all participants, and the average difficulty level for each training day for each training group separately. We initially fit a linear, exponential, and logarithmic curve to the average level reached for each training day to identify the regression equation that would best fit the data. The logarithmic regression resulted in the best fit of the averaged data by explaining the largest amount of variance,  $R^2 = .98$ . The linear regression and exponential regression explained less variance in the averaged data,  $R^2 = .82$  and  $R^2 = .89$ , respectively. Therefore, the slope of

the logarithmic regression equation was used as the learning rate for a participant across the five training days. We also extracted the intercept from these logarithmic regression equations to indicate initial participant performance in their specific training task.

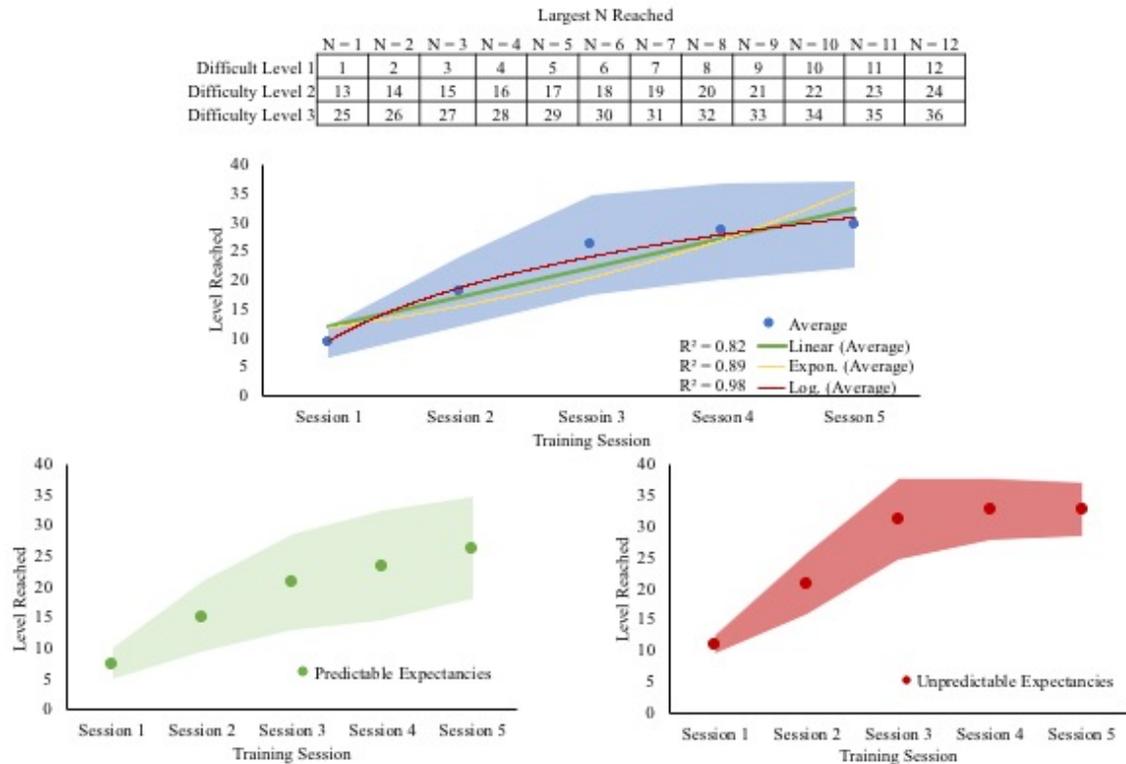


Figure 2.5. Individual learning rates, computed across all sessions, using a composite of the difficulty level and the largest N reached on each training day as the predicted variable. The slope from a logarithmic regression (shown in red), based on the composite of difficulty level and largest N reached, represents a participant’s ability to learn their particular training task. The lower two graphs indicate the variability of training performance across the two working memory training groups.

### 2.3. Results

Average reaction time for each individual and for each condition was derived from accurate trials alone. Composite scores for cognitive constructs were calculated by standardizing all measures using a normal score transformation, reverse coding reaction time and cost

measures, and averaging all standardized scores for a particular construct. The complex task measure was calculated by summing the standardized construct scores for task switching, inhibition, episodic memory, and reasoning.

The alpha level for significance was .05 and  $p$ -values were corrected for sphericity using Greenhouse-Geisser. Our effect sizes, similar to previous training studies, were expected to range from medium ( $\eta^2_p$ : .06 to .14) to large ( $\eta^2_p > .14$ ; Cohen, 1988; Tabachnick, 2001). Means and standard deviations for transfer tasks at pre-test and at immediate post-test are provided in Table 2.2, there were no group differences in any of the tasks at pre-test (all  $p > .15$ ).

### 2.3.1. Complex Task – Primary Hypothesis

In line with previous intervention studies, separate ANCOVAs were conducted for our two hypotheses and exploratory construct analyses to evaluate differences between the three groups (predictable expectancies, unpredictable expectancies, and control group) at immediate post-testing, after controlling for the individual differences in the pre-test score (Basak & O'Connell, 2016; Boot et al., 2010). For significant construct-based analyses, we also conducted repeated measures ANOVA to further investigate a time by group interaction. However, in repeated measures analyses, these time by group interactions could be due to regression towards the mean and not training effects. Therefore, to ensure that any post-training changes in performance was not due to regression towards the mean, ANCOVAs act as our primary evidence of transfer to account for any individual differences at pre-test.

The composite score for the complex task measures was a combination of task switching, inhibition, episodic memory, and reasoning tasks. The costs and reaction time measures were reverse coded, such that all measures are coded in the same direction.

Table 2.2. Transfer tasks completed by all groups at pre-test and immediately post-training

	Control Group		Predictable Expectancies		Unpredictable Expectancies	
	Pre	Immediate Post	Pre	Immediate Post	Pre	Immediate Post
Backward Span	4.98(1.23)	4.89(1.22)	4.8(1.13)	5.15(1.44)	4.8(1.03)	5.02(1.26)
Computation Span	5.36(1.76)	5.39(1.83)	5.39(1.95)	6.13(1.52)	5.59(1.33)	5.52(1.56)
Reading Span	3.91(1.66)	4.26(1.66)	3.87(1.39)	4.39(1.44)	4.09(1.44)	4.59(1.3)
Visual N-Update GC	551.55(613.49)	378.83(299.41)	788.65(637.4)	386.58(276.38)	597.82(356.1)	280.62(191.15)
Trails B - Trails A	24.73(16.51)	25.05(20.45)	27.21(13.13)	21.86(18.12)	19.2(11.08)	21.12(7.65)
CVOE GSC	878.23(290.41)	783.39(246.54)	966.95(353.86)	708.45(326.03)	913.32(262.46)	754.68(264.32)
Task Switching GSC	382.77(187.76)	340.67(161.11)	404.23(185.72)	447.18(205.14)	425.24(214.11)	371.75(138.76)
Flanker Cost	65.73(43.7)	77.74(42.86)	68.75(39.87)	61.89(46.21)	67.68(28.11)	50.5(26.54)
Simon Cost	26.75(45.93)	26.78(29.93)	36.28(45.2)	11.46(28.1)	45.48(33.2)	14.4(22.08)
Story Recall Delay	12.26(5.34)	12.26(4.94)	12.04(5.27)	15.35(3.9)	13.09(6.01)	14.95(4.61)
Associative Memory RT	1823.66(423.34)	1614.26(516.56)	1717.59(366.53)	1287.01(295.25)	1884.45(550.90)	1268.53(269.54)
RAPM Total Correct	12.13(3.55)	11.65(2.84)	12.87(2.93)	13.09(2.73)	11.74(3.05)	12.48(2.56)
Forward Span	6.67(1.28)	7.04(1.21)	7.33(1.32)	7.35(1.56)	6.87(0.96)	7.02(1.13)
DSST	23.7(3.56)	25.3(4.01)	24.17(4.37)	25.39(4.37)	23.48(3.98)	24.74(4.7)

\*GC=Global Cost, GSC=Global Switch Cost, DSST=Digit Symbol Substitution Task

The ANCOVA conducted on this composite measure found a significant difference for groups,  $F(2, 61) = 98.11, p = .001, MSE = 2.29, \eta^2_p = .21$ . This yielded a large effect of group. Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of group was driven by differences between the two training groups and the control group (both  $p < .01$ ). However, the predictable expectancies training group and the unpredictable expectancies training group did not differ in complex task scores after 10 hr of training ( $p = .89$ ). Figure 2.6 shows the post-training differences in the standardized complex task measure for the three groups, controlling for pre-test scores.

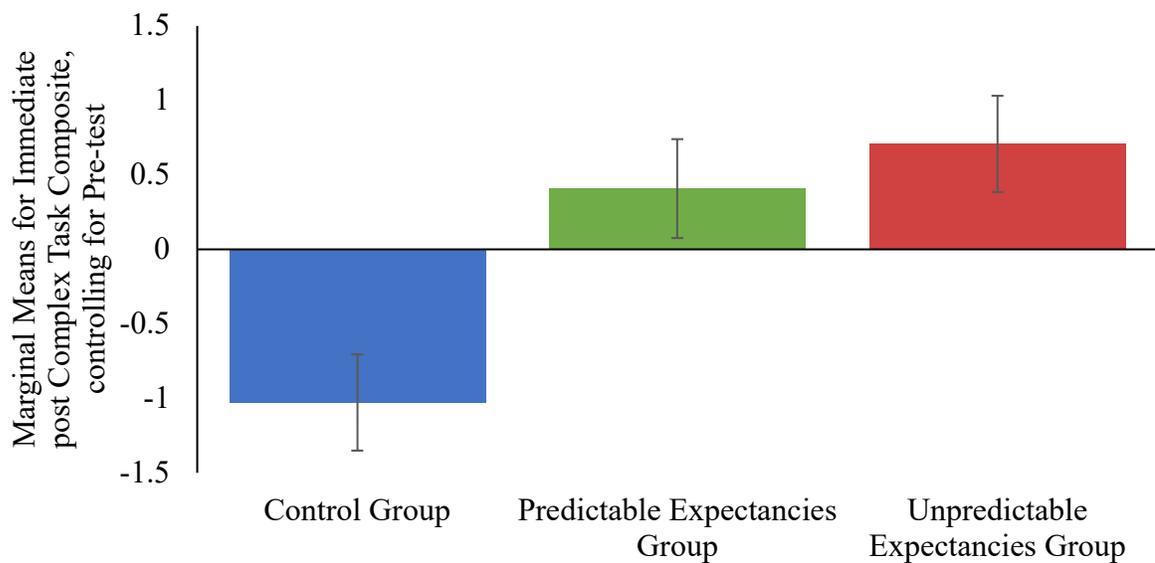


Figure 2.6. Marginal means for the standardized complex task measure at the immediate post-test session, controlling for the pre-test performances. Error bars represent standard error of the mean.

To further investigate our complex task composite, a MANCOVA was conducted to investigate the effects of group on the four constructs of complex tasks. For this analysis, we controlled for the pre-test scores in the four constructs. Using Wilks'  $\Lambda$ , there was a significant effect of training on immediate post-test performance in task switching, inhibition, episodic

memory, and reasoning tasks, Wilks's  $\Lambda = 0.67$ ,  $F(4, 55) = 3.04$ ,  $p = .004$ ,  $\eta_p^2 = 0.18$ . This yielded a large effect of group. However, the separate univariate ANCOVA's produced by this multivariate analysis revealed only two of our complex task constructs to be significant, inhibition and episodic memory,  $F(2, 58) = 7.41$ ,  $p = .001$ ,  $MSE = 0.22$ ,  $\eta_p^2 = .20$ ;  $F(2, 58) = 7.54$ ,  $p = .001$ ,  $MSE = 0.41$ ,  $\eta_p^2 = .21$ , respectively. These ANCOVAs were based on controlling for pre-test performance in all four constructs, therefore, we conducted separate ANCOVAs for the inhibition and episodic memory constructs in order to control for only the corresponding pre-test performance in that construct.

The composite score for the inhibition measure was a combination of reversed coded Simon cost and Flanker cost. The ANCOVA conducted on this measure, controlling for pre-test performance, resulted in a significant main effect of group,  $F(2, 65) = 7.92$ ,  $p = .001$ ,  $MSE = 0.37$ ,  $\eta_p^2 = .20$ . This yielded a large effect of group. Post-hoc paired comparisons using the Sidak corrections indicated that this effect was driven by differences between the training groups and the control group (both  $p < .01$ ), however, the predictable expectancies training group and the unpredictable expectancies training group did not differ in inhibition construct scores after 10 hr of training ( $p = .90$ ). Figure 2.7 shows the post-training differences in the standardized inhibition measure for the three groups, controlling for pre-test.

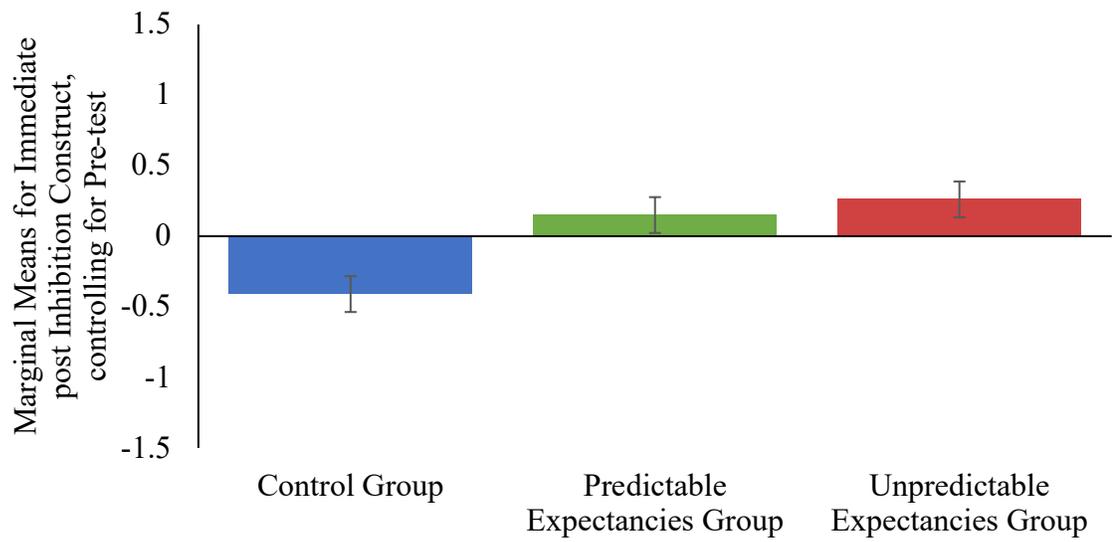


Figure 2.7. Marginal means for the standardized inhibition measure at the immediate post-test session, controlling for the pre-test performances. Error bars represent standard error of the mean.

We conducted repeated measures ANOVA to investigate the time x group interaction suggested by our ANCOVA results. A 2 (time: pre-test, immediate post-test) x 3 (group: control group, predictable expectancies group, unpredictable expectancies group) repeated measures ANOVA was conducted on the inhibition construct and resulted in a significant time x group interaction,  $F(2, 66) = 8.10, p = .001, MSE = .26, \eta^2_p = .20$ . This interaction suggests that the unpredictable expectancies group has a more drastic change in inhibition construct scores from pre-test to immediate post-test. Figure 2.8 displays the gain scores in the inhibition construct for each participant in the three groups. It is evident from this figure that the gains for individuals in the unpredictable expectancies group are more robust than both the predictable expectancies group and even more so the control group.

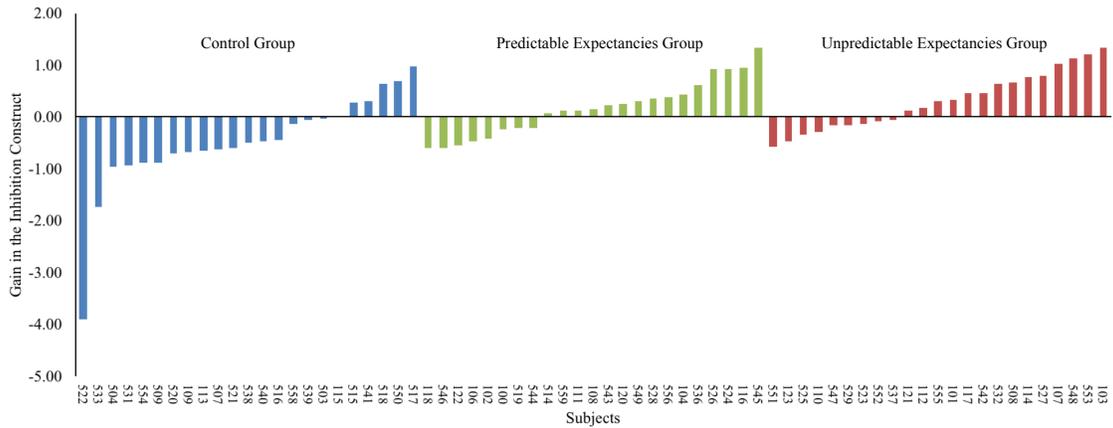


Figure 2.8. Individual differences for standardized gain scores in the inhibition construct for the control group (blue), predictable expectancies group (green), and unpredictable expectancies group (red). Positive scores indicated performance gains, and negative scores indicated performance declines after completion of training.

The composite score for the episodic memory measure is a combination of Story Recall 30-minute delay and reverse coded reaction time for Associative Memory. The ANCOVA conducted on this measure, controlling for pre-test performance, resulted in a significant main effect of group,  $F(2, 61) = 7.52, p = .001, MSE = 0.44, \eta^2_p = .20$ . This yielded a large effect of group. Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of group was driven by a significant difference between the two training groups and the control group ( $p < .01$ ). The predictable expectancies training group and the unpredictable expectancies training group did not differ in episodic memory construct scores after 10 hr of training ( $p = .96$ ). Figure 2.9 shows the standardized immediate post-training differences in the episodic memory measure for the three groups, controlling for pre-test.

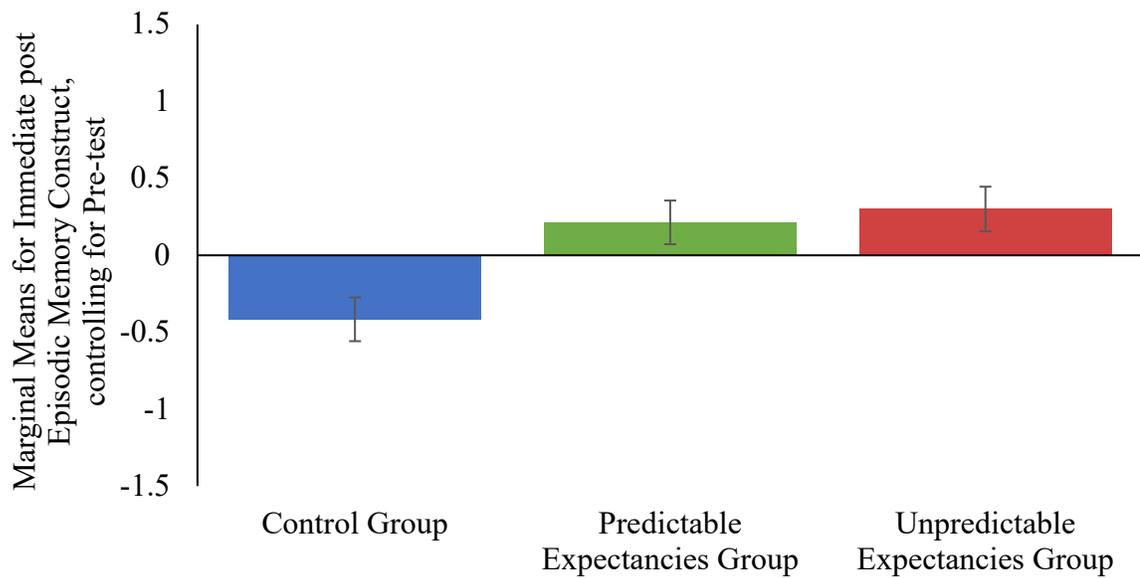


Figure 2.9. Marginal means for the standardized episodic memory measure at the immediate post-test session, controlling for the pre-test performances. Error bars represent standard error of the mean.

A 2 (time: pre-test, immediate post-test) x 3 (group: control group, predictable expectancies group, unpredictable expectancies group) repeated measures ANOVA was conducted on the episodic memory construct and resulted in a significant time x group interaction  $F(2, 62) = 5.03, p = .01, MSE = .29, \eta^2_P = .14$ . This interaction suggests that the unpredictable group has a more drastic change in standardized episodic memory construct scores from pre-test to immediate post-test. Figure 2.10 displays the gain scores in the episodic memory construct for each participant in the three groups. A visual examination of gain scores suggests more robust gains for individuals in the unpredictable expectancies group compared to both the predictable expectancies group and the control group.

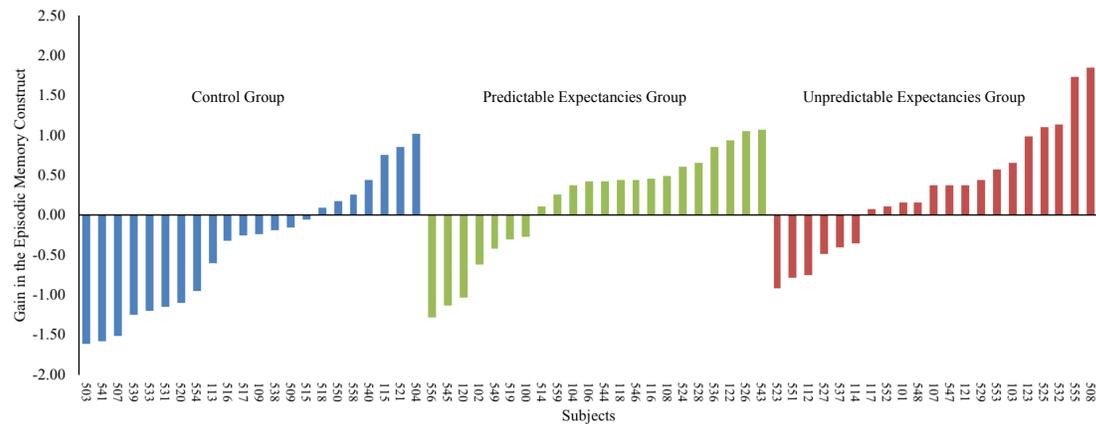


Figure 2.10. Individual differences for standardized gain scores in the episodic memory construct for the control group (blue), predictable expectancies group (green), and unpredictable expectancies group (red). Positive scores indicated performance gains, and negative scores indicated performance declines after completion of training.

### 2.3.2. Working Memory Capacity – Secondary Hypothesis

The temporal dynamics of performance in the predictable and unpredictable expectancies training tasks were investigated using Day 1 and Day 5 reaction time performance for the first four Ns. First, separate univariate repeated measures ANOVA with set-size (N = 1, 2, 3, and 4) as a factor was conducted for each training group for Day 1 performance. The main effect of N for the predictable expectancies group was significant,  $F(1.62, 30.84) = 45.50, p < .001, MSE = 3464.29, \eta^2_p = .71$ . This yielded a large effect of N. Post-hoc multiple comparisons using repeated contrasts indicated that reaction times of N = 2 were significantly slower than reaction times of N=1 by approximately 130 ms,  $F(1, 19) = 86.70, p < .001, MSE = 3919.54, \eta^2_p = .82$ . The other Ns did not differ from one another ( $p > .60$ ). In the unpredictable expectancies task, the main effect of N was significant,  $F(1.96, 41.30) = 28.67, p < .001, MSE = 4676.22, \eta^2_p = .58$ . Again, reaction times of N = 2 were significantly slower than reaction times of N = 1 by approximately 100 ms,  $F(1, 21) = 21.74, p < .001, MSE = 11914.68, \eta^2_p = .51$ . Furthermore,

reaction times of  $N = 3$  were significantly slower than reaction times of  $N = 2$ ,  $F(1, 21) = 4.54$ ,  $p = .04$ ,  $MSE = 4076.35$ ,  $\eta^2_p = .18$ . However, reaction times of  $N = 4$  were not significantly slower than reaction times of  $N = 3$  ( $p = .35$ ). Therefore, in both versions of the training task, we found evidence of focus switch costs. These costs were slightly smaller than those obtained from previous aging studies, where N-Back tasks yielded 240 – 350 ms focus switch cost (Vaughan, Basak, Hartman, & Verhaeghen, 2008; Verhaeghen & Basak, 2005) and random N-back yielded approximately 500 ms cost (Basak & Verhaeghen, 2011a). This may be due to the time restraint placed on responses in the current training tasks and the younger adult sample used in the current study compared to the older adult sample used in others.

To evaluate whether the focus of attention expanded with 10 h of practice, defined by a shift in the magnitude of focus switch cost, we conducted separate univariate repeated measures ANOVA with set-size ( $N = 1, 2, 3$ , and 4) as a factor for each training group for Day 5 performance and then conducted separate, planned paired-samples  $t$ -tests to investigate whether focus switch costs differed between Day 1 and Day 5 of training for the two training groups. The main effect of  $N$  for the predictable expectancies group was significant at Day 5,  $F(1.39, 26.48) = 41.82$ ,  $p < .001$ ,  $MSE = 2825.42$ ,  $\eta^2_p = .69$ . This yielded a large effect of  $N$ . Post-hoc multiple comparisons using repeated contrasts indicated that reaction times of  $N = 2$  were significantly slower than reaction times of  $N = 1$  by approximately 50 ms,  $F(1, 19) = 22.65$ ,  $p < .001$ ,  $MSE = 2810.53$ ,  $\eta^2_p = .54$ . Furthermore, reaction times of  $N = 3$  were significantly slower than reaction times of  $N = 2$  by approximately 40 ms,  $F(1, 19) = 37.63$ ,  $p < .001$ ,  $MSE = 931.13$ ,  $\eta^2_p = .66$  and reaction times of  $N = 4$  were significantly slower than reaction times of  $N = 3$  by approximately 20 ms,  $F(1, 19) = 20.63$ ,  $p < .001$ ,  $MSE = 400.16$ ,  $\eta^2_p = .53$ . In the unpredictable expectancies

task, the main effect of N was also significant,  $F(2.45, 51.42) = 44.78, p < .001, MSE = 3019.43, \eta^2_p = .68$ . Again, reaction times of N = 2 were significantly slower than reaction of N=1 by approximately 100 ms,  $F(1, 21) = 32.18, p < .001, MSE = 4434.59, \eta^2_p = .61$ . Furthermore, reaction times of N = 3 were significantly slower than reaction times of N = 2 by approximately 70 ms,  $F(1, 21) = 15.72, p = .001, MSE = 6873.86, \eta^2_p = .43$ ; however, the reaction times of N = 4 were not significantly slower than reaction times of N = 3,  $p > .82$ . The post hoc analyses of the two Day 5 ANOVAs suggest a change in focus switch cost, particularly for the predictable expectancies group from 130 ms to 50 ms. This was further investigated by running separate paired-samples *t*-tests for the two training groups comparing Day 1 and Day 5 focus switch costs. Focus switch cost was calculated by subtracting N = 1 reaction time from the average of N > 1 reaction times. Although only trending toward significance, the predictable expectancies training group seems to reflect a decrease in focus switch cost following 10 hr of training,  $t(17) = 2.01, p = .06$ . In contrast, the unpredictable expectancies training did not change focus switch cost after 10 hr of training,  $t(20) = .19, p = .85$ .

The results from our multiple ANOVAs did not indicate an expansion in focus of attention, as indicated by significant differences between N=1 and N=2 for both training groups following 10 hr of training. However, the focus switch cost analyses suggest that predictable expectancies training decreases focus switch cost more so than the unpredictable expectancies training. Figure 2.11 illustrates the change in reaction time for the two training groups across N and training day.

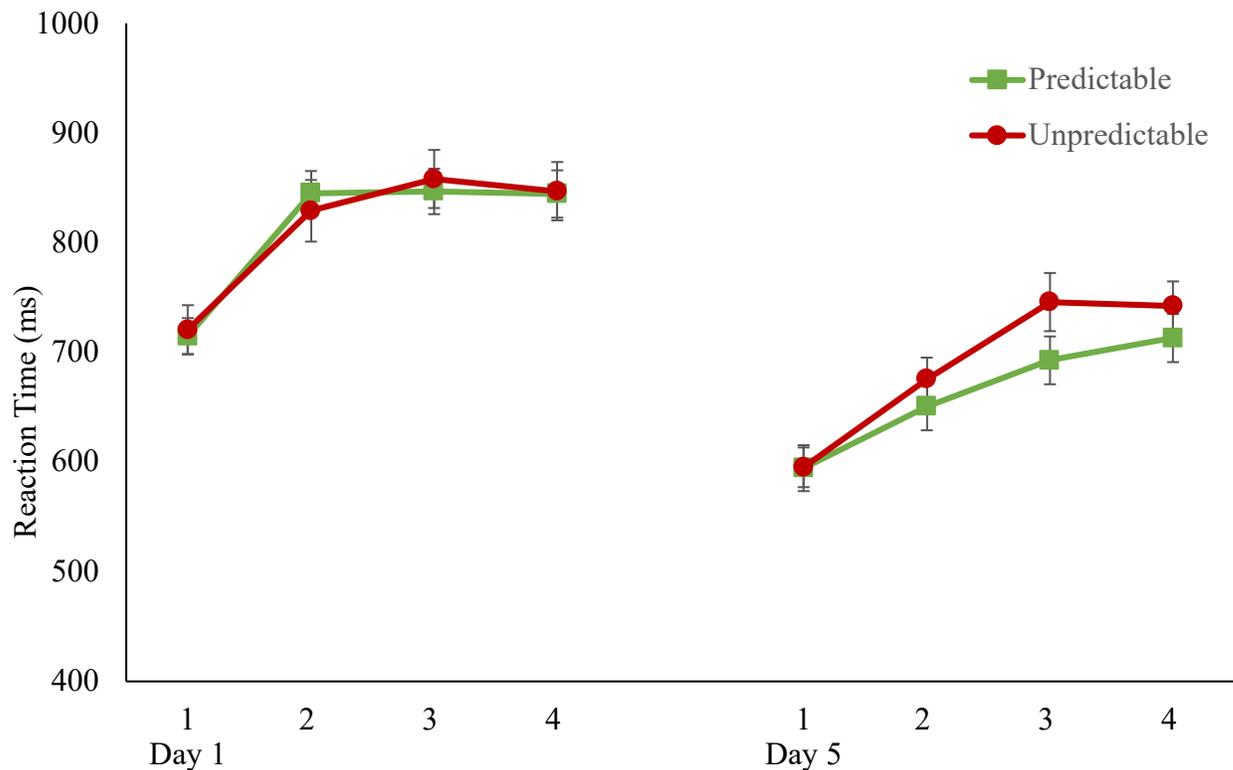


Figure 2.11. Training-related changes in reaction time (in ms) from Day 1 to Day 5 of training. Both training groups decreased in reaction time, reflecting increased efficiency in probe retrieval. However, only the predictable expectancies group resulted in a marginally significant decline in the focus switch cost ( $N>1$  minus  $N=1$ ) from Day 1 to Day 5 of training. Error bars represent standard error of the mean.

Our secondary hypothesis was that any expansion of the focus of attention for the predictable expectancies group would translate to greater transfer to a working memory capacity construct. Although our multiple ANOVAs did not indicate any expansion, the decrease in focus switch cost for the predictable training group, but not unpredictable training group, suggests possible, albeit minor, expansion for the predictable group. Thus, the composite score for the working memory capacity measure was a combination of the backward span task, reading span task, and computational span task. However, the ANCOVA conducted on this measure,

controlling for pre-test performance, found that the main effect of group was not significant,  $F(2, 65) = 1.18, p = .31, MSE = 0.43, \eta^2_P = .04$ .

### 2.3.3. Exploratory Analyses

#### 2.3.3.1. Additional Constructs

We had three addition measures, one working memory updating, one short-term memory, and one processing speed. We did not hypothesize any training-related benefits for tasks of short-term memory or processing speed. Our results from separate ANCOVAs supported this hypothesis (forward span:  $F(2, 65) = 0.16, p = .85, MSE = 0.63, \eta^2_P = .005$ ; DSST:  $F(2, 65) = 0.25, p = .78, MSE = 0.22, \eta^2_P = .008$ ). The Visual N-Update task was the most similar task to the trained working memory tasks, therefore we hypothesized that if anything, both training groups would improve in the working memory updating task measure in comparison to the control group. However, the ANCOVA conducted on this measure, controlling for pre-test performance, found that the main effect of group was not significant,  $F(2, 63) = 1.56, p = .22, MSE = 0.72, \eta^2_P = .05$ .

#### 2.3.3.2. Individual Differences

In order to investigate the effect of individual differences on transfer, we first conducted multiple one-way ANOVAs and independent samples t-tests on demographic, pre-test, and training-related variables, to investigate any group differences. Our results indicated that groups did not differ in demographics or pre-test performance, however, the predictable expectancies training group and unpredictable expectancies training group were significantly different in learning rate for the trained tasks ( $t(44) = -2.55, p = .01$ ) and initial performance in the trained tasks ( $t(44) = -4.94, p < .001$ ). These variables were extracted from the logarithmic functions fit

to individual performance in all sessions of training. Participants were assigned to a group based on their learning rate or initial performance using a median split by group. Multiple ANCOVAs were conducted on these new groups to investigate whether individual differences in learning affect transfer to the complex task composite, inhibition construct, and episodic memory construct.

#### 2.3.3.2.1. Individual Differences in Learning Rate

An ANCOVA conducted on the complex task composite, controlling for pre-test performance, resulted in a significant main effect of learning rate group,  $F(4, 59) = 4.90, p = .002, MSE = 2.26, \eta^2_p = .25$ . This yielded a large effect of learning rate group. Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of learning rate group was driven by a significant difference between the high performers in the unpredictable expectancies group and the control group ( $p = .001$ ). There were no differences found between any of the working memory training groups, including differences between high and low performers.

An ANCOVA conducted on the inhibition construct, controlling for pre-test performance, resulted in a significant main effect of learning rate group,  $F(4, 63) = 5.73, p = .001, MSE = 0.35, \eta^2_p = .27$ . This yielded a large effect of learning rate group. Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of learning rate group was driven by a significant difference between the high performers in both the predictable and unpredictable expectancies groups and the control group ( $p < .004$ ). There were no differences found between any of the working memory training groups, including differences between high and low performers.

An ANCOVA conducted on the episodic memory construct, controlling for pre-test performance, resulted in a significant main effect of learning rate group,  $F(4, 59) = 3.95, p = .01, MSE = 0.45, \eta^2_p = .21$ . This yielded a large effect of learning rate group. Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of learning rate group was driven by a significant difference between the high performers in the unpredictable expectancies group and the control group ( $p = .01$ ). There were no differences found between any of the working memory training groups, including differences between high and low performers.

#### 2.3.3.2.2. Individual Differences in Initial Performance

An ANCOVA conducted on the complex task composite, controlling for pre-test performance, resulted in a significant main effect of initial performance group,  $F(4, 59) = 4.92, p = .002, MSE = 2.25, \eta^2_p = .25$ . This yielded a large effect of initial performance group. Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of initial performance group was driven by a significant difference between the high performers in both the predictable expectancies and the unpredictable expectancies groups and the control group ( $p < .02$ ). There were no differences found between any of the working memory training groups, including differences between high and low performers.

An ANCOVA conducted on the inhibition construct, controlling for pre-test performance, resulted in a significant main effect of initial performance group,  $F(4, 63) = 3.95, p = .01, MSE = 0.38, \eta^2_p = .20$ . This yielded a large effect of initial performance group. Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of initial performance group was driven by a significant difference between both the low and high performers in the unpredictable expectancies group and the control group ( $p < .03$ ). The difference between high

performers in the predictable expectancies group and the control group was trending in the right direction ( $p = .05$ ). There were no differences found between any of the working memory training groups, including differences between high and low performers.

An ANCOVA conducted on the episodic memory construct, controlling for pre-test performance, resulted in a significant main effect of initial performance group,  $F(4, 59) = 3.83$ ,  $p = .01$ ,  $MSE = 0.45$ ,  $\eta^2_p = .21$ . This yielded a large effect of initial performance group. Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of initial performance group was driven by a significant difference between the high performers in unpredictable expectancies group and the control group ( $p = .02$ ). There were no differences found between any of the working memory training groups, including differences between high and low performers.

#### 2.3.3.3. Training Efficacy

Twenty-three participants completed a post hoc questionnaire where they indicated whether they enjoyed the task, whether they used specific strategies, and whether they felt as though their cognition changed as a result of the training. Participants in the predictable and unpredictable training groups did not differ in their perception of whether their cognition changed following training,  $t(21), -.73, p = .47$ . Both groups indicated that they were unsure of whether the training improved their cognition.

## 2.4. Discussion

Past studies are mixed in their findings on transfer following working memory training in the construct and magnitude of change (Au et al., 2015; Harrison et al., 2013; Karbach & Verhaeghen, 2014; Klingberg, 2010; Morrison & Chein, 2011; Shipstead et al., 2012). The

current study predicted that this was due to the differences in internal task demands during different training protocols. To confront this issue, we directly compared training in the same working memory updating task with one between-group difference: probe-cue expectancies.

#### 2.4.1. Primary Hypothesis

The primary hypothesis of the current study was that training in a working memory task with unpredictable expectancies would bias the reactive control system proposed by Braver and colleagues (2007) and transfer to complex tasks, over and beyond that of predictable expectancies training and an active control group. Our predictions were based on the combination of findings and theories from the Theory of Working Memory Adaptability model (Basak & Zelinski, 2012) and the Dual Mechanism Framework of Cognitive Control (Braver, 2012). However, based on the current methodology, we failed to support our primary hypothesis. Our results found larger improvements in a composite score of complex tasks for both working memory training groups in comparison to the control group. When the cognitive constructs that were aggregated to create the complex task measure were investigated separately, this same pattern of benefits to both working memory training groups was found for the inhibition and episodic memory constructs. Furthermore, across all analyses conducted, the predictable expectancies training group did not differ in magnitude of transfer from the unpredictable expectancies group.

The current study was similar to, but not a replica, to the study conducted by Basak and O'Connell (2016). The methodology for the current training tasks was individualized adaptive, provided feedback, and increased the possible memory load to  $N = 12$ . The increase in possible memory load, in particular, seems to affect the underlying control mechanism utilized in the

tasks. For instance, in prior working memory updating training studies, which used the N-back task or modifications of the N-back task, the memory load often maximized at four, in compliance with Cowan's hypothesized working memory capacity (Cowan, 2001). In an individualized adaptive training using the dual N-back task, the maximum average memory load across twelve days of training was six (Colom et al., 2013). In the current study, participants in both conditions frequently surpassed these memory loads. This leads us to believe that our framework of biasing proactive and reaction control to predictable and unpredictable expectancies may be dependent on the memory load. For instance, the AX-CPT task, which is commonly used in the Dual Mechanisms Framework of Cognitive Control includes only four trial types; the errors of two of these trials (AX and BX) act as the proxy for the specific type of control being used (Braver, Paxton, Locke, & Barch, 2009). Although previous research has suggested that training can bias a participant toward proactive control strategies (Gonthier, Macnamara, Chow, Conway, & Braver, 2016), this was only investigated using the AX-CPT task. The training protocol for both working memory groups in the current study employed difficulty levels and maximum set-sizes that far exceeded the demands on control used during the AX-CPT task.

Speer, Jacoby, and Braver (2003) investigated the effect of memory load on the Dual Mechanisms Framework using the Sternberg item recognition task (Sternberg, 1966). This study manipulated memory load expectations by having participants perform task blocks where memory load varied by trial. There were two types of task blocks, one low memory load block, with an average of three items to be maintained, and one high memory load block, with an average of eight items to be maintained. Within both of these task blocks, twenty-five percent of

the trials were a memory load of six items. These trials were compared to investigate how memory load expectation would bias the control mechanisms relied upon for task performance. Results indicated that a quick target detection process was used in the low load block, whereas deeply encoded retrieval cues were used in the high load block. Thus, memory load expectation varied the control process used, with low load blocks biasing proactive control and high load blocks biasing reactive control, even on trials with equal memory loads (six items). Brain activation of the PFC supported these dissociations. Regions in the medial and mid-lateral PFC progressively increased activation through the encoding and delay period for the low memory load condition. In contrast, these same regions rapidly increased activation during encoding, but remained stable throughout the delay period for the high memory load condition. During the probe judgement, anterior PFC regions activated significantly more for the high memory load condition. This general region, the anterior PFC, is related to episodic retrieval processes (Lepage, Ghaffar, Nyberg, & Tulving, 2000). In the current study, it is possible that participants in the predictable expectancies group relied upon a proactive control process until they were unable to do so, seemingly once working memory capacity was exceeded, and then switched to a reactive control process. Thus, although we predicted specific relationships between predictable and unpredictable expectancies and constructs of transfer, the preference toward proactive or reactive control could have been seemingly equal for set-sizes outside of the working memory capacity and biased toward reaction control for both expectancies groups. This bias resulted in significant transfer to the complex task measures for both working memory training groups, compared to control.

The analyses conducted for the primary hypothesis may have failed to find statistical support, however, our novel approach to investigate individual differences does suggest that our primary hypothesis still holds merit. For instance, the visualizations of gain scores across the inhibition construct (Figure 2.8) and episodic memory construct (Figure 2.10) indicated more robust gains in favor of the unpredictable expectancies group compared to the predictable expectancies group and control group. Furthermore, we conducted individual differences analyses based on measures with individual variability. The two training groups differed in two training-related measures: learning rate and initial performance, with the unpredictable expectancies group resulting in faster learning and higher initial performance. This difference is likely due to the within-task elements previously identified. Thus, we split the individuals in each training group into high and low performers according to their own group median score in the particular variable of investigation. These individual differences analyses found performance group to significantly affect transfer, particularly in favor of the unpredictable expectancies group.

The analyses conducted on the groups that were created based on learning ability in the training tasks, shows the Matthew Effect, also known as the magnification or amplification effect, on transfer to the complex task composite, inhibition construct, and episodic memory construct (Kliegl, Smith, & Baltes, 1990; Lövdén, Brehmer, Li, & Lindenberger, 2012; Verhaeghen & Marcoen, 1996). The Matthew Effect was named after a passage from the Bible, which stated the following, “Whoever has will be given more, and they will have an abundance” (Matthew 13:12, New International Version). This suggests that an individual with higher abilities, will result in more benefits from training. The Matthew Effect is often cited as the

reason why younger adults gain more from certain interventions than older adults, due to the initial impairments in older adults compared to younger adults. Our results suggest that individuals who learned the trained task faster, or the high performers, specifically in the unpredictable expectancies training group, resulted in significantly more transfer to the complex task composite, inhibition construct, and episodic memory construct, compared to the control group. The Dual Mechanisms Framework finds neural regions which underlie both episodic memory (MTL) and inhibition (ACC) to be activated during tasks of reactive control. Thus, individuals who are good learners in a task biasing reactive control, resulted in more robust transfer to tasks with similar neural mechanisms. This result, albeit with high performers, is in line with our primary hypothesis.

Working memory training, however, has mixed results of the Matthew Effect, with many studies resulting in a compensatory effect for low performers following training (Jaeggi, Buschkuhl, Jonides, & Perrig, 2008; Karbach & Kray, 2009; Zinke et al., 2014). A compensatory effect finds initially low performers to have more room to improve, compared to initially high performers, and thus larger gains in transfer following training (Lee et al., 2012; von Bastian & Oberauer, 2013). Our results from the analyses using initial performance in the training tasks as a grouping variable suggests a training specific benefit for the inhibition construct. Both the high and low performers in the unpredictable expectancies training group significantly improved in from the inhibition measure following training, in comparison to the control group. Our results suggest that this is not a compensatory effect, due to the significant results for the high performers, along with the low. However, the lack of significance for the predictable expectancies group does suggest that implementing the unpredictable expectancies

training to initially low performers will have greater benefits than choosing to implement the predictable expectancies training. This is an important finding for future research in populations with low initial cognition. By grouping our participants by performance, we were able to illustrate our hypothesized direction of transfer in favor of the unpredictable expectancies group, compared to the null findings for the predictable expectancies group.

Transfer to the inhibition construct for the high and low initial performers in the unpredictable expectancies group, compared to the control group, is to be expected due to the current gamified task including both location and identity as cues for comparison. Past bird identities and birds on un-probed trees compete for retrieval in both the predictable and unpredictable training tasks. However, the unpredictable training relies upon reactive control across all memory loads, and we surmise that predictable training only relies upon these mechanisms in memory loads outside of the working memory capacity. Thus, training in a task where learning to inhibit retrieval of interfering items is necessary to successfully perform the task, regardless of initial performance, will result in greater transfer to tasks with similar inhibitory mechanisms.

#### 2.4.2 Secondary Hypothesis

The secondary hypothesis of the current study was that training in a working memory task with predictable expectancies would expand the focus of attention and bias the proactive control system proposed by Braver and colleagues (2007) and transfer to tasks of working memory capacity, over and beyond that of unpredictable expectancies training and an active control group. Our findings suggest that predictable expectancies involve less cognitive control than unpredictable expectancies but only within the working memory capacity (N=4). Figure 2.7

supports this finding, indicating that learning in the predictable group is faster than learning in the unpredictable group. Although we were unable to provide evidence for an expansion of the focus of attention to an N of 4, like previous studies (Verhaeghen et al., 2004), the predictable expectancies training group resulted in marginal differences between the focus switch cost on Day 1 and Day 5 of training. However, this suggested expansion of the focus of attention did not translate to improvements in tasks of working memory capacity.

#### 2.4.3 Participant Training Experience

*“It made my brain melt with boredom” - Participant*

*“I would have played this game if I had it on my phone all the time. Not particularly because I like birds (I’m scared of birds in real life), but I found the outcome interesting and wanted to score higher and remember more every time.” - Participant*

It is unsurprising that participants had a mixed relationship with the training task. In a post hoc questionnaire conducted on 23 of the working memory training participants, individuals indicated whether they enjoyed the task, whether they used specific strategies, and whether they felt as though their cognition changed as a result of the training. The quotes above are two examples of participant responses to their enjoyment of the task. In line with this mixed perception of the task itself, participants in the predictable and unpredictable training groups did not differ in their perception of whether their cognition changed. When asked whether they used a specific strategy, most participants indicated that they identified the birds using verbalization of color, type, or names. Interestingly, when the participants were asked whether they noticed any patterns in the tasks, the two training groups prioritized different task elements. The unpredictable expectancies training group discussed the tree presentation order, whereas the

predictable expectancies training group discussed the bird identity order. These focal differences make us hesitant to suggest that the predictable training group perceived the underlying task pattern, thus suggesting another reason why they may not have prioritized a proactive control strategy. Unfortunately, the number of participants who completed this questionnaire was quite low, as it was introduced part-way into our research design, and we could not use this information in our individual differences analyses.

The current study intended to investigate whether probe-cue expectancies was an optimal within-task manipulation to enhance transfer effects, particularly to complex tasks. According to the Theory of Working Memory Adaptability model and Dual Mechanisms Framework of Cognitive Control, a bias toward reactive control mechanisms during unpredictable working memory tasks would rely upon long-term memory and executive control systems (Basak & Zelinski, 2012; Braver, 2012). Training in an unpredictable task would accordingly transfer to tasks of long-term memory and cognitive control (e.g., task-switching and inhibition). We believe that the increase in memory load for our training tasks biased both the predictable and unpredictable expectancies groups toward reactive control mechanisms outside of the working memory capacity, thus resulting in global benefits to both working memory training groups. However, when implementing a novel approach to investigate individual differences, we found that initially high performers and fast learners in the unpredictable expectancies training group did result in robust improvements for tasks of these cognitive constructs, compared to the active control group. Whereas, these same findings in favor of individuals in the predictable expectancies training were limited. In the future, a set maximum N within the working memory capacity may allow for the predictable expectancies group to optimally preplan retrieval of

comparative items and bias proactive control. This may bifurcate the direction and magnitude of transfer for the two training groups, resulting in transfer to all complex tasks for both high and low performers in the unpredictable expectancies group, compared to the predictable expectancies group, as originally hypothesized and tested in our main analyses. Finding an optimal strategy to enhance cognition is important for future development of cognitive training, especially when these findings could augment cognitive training strategies for older adults. Our findings benefiting low performers in the unpredictable expectancies group suggests that this task could be the most beneficial for populations with working memory deficits, such as older adults or children. The results from Basak and O'Connell (2016) come from an older adult sample and show this robust effect of unpredictable, over predictable, expectancies training for transfer to untrained constructs of cognition. Together, these results suggest a promising tool for individuals with cognitive deficits, however, more studies must be conducted.

## **CHAPTER 3**

### **EXPERIMENT 2**

#### 2.1. Rationale

Learning a new skill requires specific cognitive abilities and neural engagement. Individual differences in baseline strengths and weaknesses within cognitive constructs have been found to relate to how easily an individual acquires a new skill (Macnamara, Hambrick, & Oswald, 2014). Less is known about how inter-connectivity of the brain affects an individual's ability to acquire a new skill. Thus, the relationship between skill-learning and functional networks is very limited. The current study investigated the relationship between learning of two different complex tasks and functional connectivity of attentional networks during three different cognitive control tasks. This novel approach specifically results in regions of connectivity that relate to faster learning in the two types of casual games, which represent our complex tasks. Furthermore, the three cognitive control tasks vary in complexity, which is manipulated by systematically increasing cognitive control demands (as in O'Connell & Basak, 2018). Therefore, we could determine if the connectivity-learning relationship differs across these three different tasks. Implementation of a broad age range in the current study also allowed us to investigate whether the resulting patterns differ between younger and older adults. This study is novel in its use of varying task complexity and age groups, and the methodological approach used to investigate how two types of complex tasks differentially predict task-related functional connectivity of the attentional networks.

### 2.1.1. Attentional Networks

Researchers have previously implemented resting-state connectivity and task-related connectivity to highlight two networks that support mechanisms of cognitive control: the fronto-parietal (FP) and cingulo-opercular (CO) networks (Dosenbach et al., 2007; Power et al., 2011). In the current study, we selected seeds for functional connectivity from regions within these two attentional networks, CO and FP. These attentional networks are hypothesized to be different, with the CO network associated with stable activation for task completion and the FP network associated with flexible switching of information (Dosenbach et al., 2007; Laird et al., 2011; Owen et al., 2005).

Regions within the FP network have been shown to be involved in working memory performance and cue-response mapping adaptation (Dosenbach et al., 2007; Laird et al., 2011; Owen et al., 2005). In a study that measured the regional activation during three tasks with increasing cognitive control – a simple pattern match task, a delayed match task, and a delayed alternating-match task, Klingberg, O’Sullivan, and Roland (1997) found significant activation in frontal and parietal regions for the delayed match task and delayed alternating-match task, over and beyond rest. The delayed alternating-match task, compared to the delayed match-task, resulted in even more robust activation in the frontal and parietal regions, suggesting that an increase in task difficulty increases FP region activation. FP network connectivity has also been found during working memory updating tasks, such as the standard 2-back task (Leech, Kamourieh, Beckmann, & Sharp, 2011) and the unpredictable 2-back task (O’Connell & Basak, 2018).

In contrast, the second attentional network of investigation, the CO network, is involved in top-down control of task maintenance (Dosenbach et al., 2006; Johnston, Levin, Koval, & Everling, 2007; Voss et al., 2012). Posner and Petersen identified the CO network as the core task-set system, with activation indicating the start-cue of a task and sustaining activation until the end of a task (Posner & Petersen, 1990). Furthermore, a study conducted by Weissman and colleagues suggests that the extent of activation in CO regions could indicate that a more difficult cognitive control task is starting and where to focus attention for task relevant information (Weissman, Gopalakrishnan, Hazlett, & Woldorff, 2005)

The distinction of control-type for the FP and CO networks was supported by a study that investigated the effect of video game training strategies (fixed vs. variable shifts in task priorities) on changes in functional connectivity in the CO, FP, and default mode (DM) networks in younger adults after 20 hr of training (Voss et al., 2012). Using a seed-to-voxel connectivity approach, Voss et al. found that individuals who trained in a video game that emphasizes switching task priorities unpredictably (i.e., variable priority training) resulted in significantly more connectivity for the seed of the FP network to several regions in the temporal cortex, namely those involved in the declarative learning system. In contrast, individuals who trained in the game with a fixed task priority, or the final game score, resulted in significantly more connectivity for the seed of the CO network to several regions in the temporal cortex, namely those involved in the procedural learning system. These results suggest complementary changes in connectivity to those required by the tasks themselves. For instance, the fixed priority training required motor sequences for all parts of the game and this relates to the resulting changes in connectivity to the procedural learning system. The variable priority training required stimuli-

response mapping for individual parts of the game and this relates to the resulting change to the declarative learning systems. The resulting seeds with significant connectivity for specific trainings align with the roles of the FP and CO networks in cognitive control. The FP network, significant for variable priority training, is found in flexible switching and the CO network, significant for fixed priority training, is found in top-down processing for task completion (Dosenbach et al., 2007).

Although distinct, there is also evidence of between-network communication between the FP and CO networks. This between-network connectivity is suggested to underlie most cognitive control processes, such that the FP network supports changes in stimulus modality, value, or other features and the CO network supports top-down control in the task (Dosenbach et al., 2007). Between-network connectivity has been found during the more complex conditions of task-switching (switch condition, Stelzel, Basten, & Fiebach, 2011; dual task blocks, O'Connell & Basak, 2018), and during working memory updating (O'Connell & Basak, 2018). Furthermore, the extent of between-network connectivity for our two investigated attentional networks, FP and CO, increase with task-difficulty (Dove, Pollmann, Schubert, Wiggins, & von Cramon, 2000; Klingberg et al., 1997; O'Connell & Basak, 2018).

#### 2.1.1.1. Age-related Changes in Functional Connectivity

Functional networks are found to dedifferentiate with age, indicated by disruption in the segregation of network regions and increased integration between different network regions (Damoiseaux, 2017). The attentional networks have been found to decrease in overall within-network connectivity for older adults (Allen et al., 2011; Andrews-Hanna et al., 2007; Campbell, Grady, Ng, & Hasher, 2012; Huang et al., 2015; Madden et al., 2010; Onoda, Ishihara, &

Yamaguchi, 2012; Tomasi & Volkow, 2012) and this decrease in within-network segregation has been coupled with increases in between-network integration. For instance, Grady et al. (2016) and Spreng et al. (2016) have shown that older adult connectivity of the FP, DM, and dorsal attentional networks decrease in within-network connectivity, but increase in between-network connectivity. Chan et al. (2014) has extended this finding using graph theory to illustrate decreases in network segregation not only for specific networks, but also across the whole brain system. Furthermore, a longitudinal study found a parabolic trend for between-network connectivity for the attentional networks and DM network over time (Ng, Lo, Lim, Chee, & Zhou, 2016). Ng et al. (2016) found that network segregation is highest around 40 years of age and continues to decrease after that. Network changes, specifically increases in between-network interactions, may be an automatic reaction to disruption in within-network connectivity.

The cognition-connectivity relationship for within-network changes with age indicates a decrease in within-network connectivity that is coupled with decreases in cognition (Andrews-Hanna et al., 2007; Chan et al., 2014; Damoiseaux & Greicius, 2009; Persson, Lustig, Nelson, & Reuter-Lorenz, 2007; Wang, Li, Metzak, He, & Woodward, 2010). Research conducted by O'Connell and Basak (2018) found that older adults' connectivity during a working memory updating task, in comparison to younger adults, was greater between seeds of the FP, CO, and DM networks to frontal brain regions. This increased connectivity was associated to poorer task performance in the working memory updating task and was non-compensatory for older adults (O'Connell & Basak, 2018).

### 2.1.2. Individual Differences in Learning Related Changes in Functional Connectivity

Studies focusing on individual differences in learning have explored how participant's functional connectivity at rest relates to their ability to learn not only basic-perceptual tasks (Baldassarre et al., 2012) but also in a more cognitively demanding, working memory task (Yamashita, Kawato, & Imamizu, 2015). The methodological approaches used to investigate how learning relates to functional connectivity tells us more about the interaction between individual differences and how they relate to functional network connectivity. For instance, individuals' baseline resting state connectivity within the visual cortex and between the visual cortex and higher-order cognitive regions was used to predict how well an individual would be able to learn a novel visual discrimination task (Baldassarre et al., 2012). This study suggests that resting-state connectivity patterns, related to an out-of-scanner task, can relate to the predisposition for learning. This indicates a neural marker of individual difference, specifically for learning novel perceptual tasks.

Yamashita, Kawato, and Imamizu (2015) used another methodological approach, a multivariate contribution ratio analysis, to investigate the contribution of different networks to learning of a 3-back working memory task. The largest contribution to a plateau of learning in the 3-back task was within-network connectivity of the left FP network. Furthermore, between-network connectivity of the 'middle frontal and parietal network' and 'lateral temporal network', which have been found to activate during working memory tasks, also significantly contributes to the plateau of learning in the 3-back task. This study illustrates the importance of the FP network in learning of working memory tasks. Therefore, training in tasks that utilize the FP

network could help strengthen working memory performance, which is important in populations with impaired cognition.

In the current study, we hypothesized that attentional network connectivity during tasks with unpredictable probe-cue expectancies will be related to learning of complex tasks with similar underlying cognitive demands, similar to the findings in Yamashita et al. (2015). With this goal, we used a novel approach to understand how individual differences in learning rates for two different genres of casual video games relates to connectivity in three tasks with varying complexity. This approach involved calculation of learning rates from the game scores of two genres of casual games (one action and one strategy), and then using the learning rates as predictors in task-based seed-to-voxel functional connectivity in order to understand how an individual's ability to learn differentially predicts connectivity in tasks requiring minimal, moderate, and complex cognitive control.

### 3.1.3 Casual Video Games

Baniqued et al. (2013) studied the relationships between a large corpus of casual games and cognitive abilities. They conducted a principal components analysis on 20 games, separating the games into five-components. The authors identified these components as pertaining to working memory and reasoning, spatial reasoning, attention, and two components of perceptual speed and visual-motor mechanisms. These components were then correlated with five cognitive constructs, identified via confirmatory factor analysis as working memory, fluid intelligence, perceptual speed, episodic memory, and attention. Sushi-Go-Round, the strategy game selected in the current study, separated into the working memory/reasoning component and was found to relate to tasks of working memory, attention, and episodic memory (Baniqued et al., 2013). The

current action-based game, Tank Attach 3D, is similar to the games Enigmata and Dodge, which were studied in Baniqued et al. (2013). Enigmata separated onto the spatial reasoning component, whereas Dodge separated onto the perceptual speed component. Therefore, we hypothesize that the action game used in the current study is related to spatial reasoning and perceptual speed.

The current study is novel in the investigation of how learning of these different genres of casual games relates to brain connectivity in the attentional networks during tasks of cognitive control. Using this approach, we compared the resulting maps of connectivity to understand specific learning-related differences between a complex task which relied more on spatial reasoning and perceptual speed mechanisms (that is, the action game) and a complex task which required more working memory, attention, and episodic memory mechanisms (that is, the strategy game). Furthermore, previous evidence suggests that functional networks change with increasing age (Allen et al., 2011; Andrews-Hanna et al., 2007; Campbell, Grady, Ng, & Hasher, 2012; Huang et al., 2015; Madden et al., 2010; Onoda, Ishihara, & Yamaguchi, 2012; Tomasi & Volkow, 2012), therefore, the relationship between learning in the two casual tasks may differentially predict functional connectivity during tasks of varying cognitive control for older adults, compared to younger adults.

In the current study we first investigated how two types of game learning, indexed by learning rates, differentially predicted seed-to-voxel connectivity during tasks of increasing cognitive control. We hypothesized that both complex tasks would predict increasing between network coupling with increased task complexity, as found in previous task difficulty studies (O'Connell & Basak, 2018, Yamashita et al., 2015). Furthermore, we hypothesized that strategy

game learning would be related to functional connectivity for the attentional networks during the two in-scanner tasks that required cognitive control components of updating and/or unpredictable expectancies (Dual task and Memory Updating). In contrast, action game learning would be related to connectivity for the attentional networks during the in-scanner tasks which required maintenance and/or unpredictable expectancies (Single task and Dual task). Subsequently, we hypothesized that older adults, compared to younger adults, would result in a limited relationship between learning in both complex tasks and functional connectivity – regardless of task and network. The current study allowed us to investigate how learning predicts differences in brain connectedness during cognitive control tasks with varying complexity. In line with previous learning studies, the results can indicate regions that better learners in different complex tasks coactivate during performance of different cognitive control tasks.

## 2.2. Method

### 2.2.1. Recruitment

Participants were recruited from the Dallas/Fort Worth metroplex and the University of Texas at Dallas using advertisements and flyers. Fifty-six individuals met inclusion criteria and were used in the current study; four of these individuals were removed from analysis due to recording errors during the scan. The final analyses included 23 younger adults ( $M_{age} = 25.70$ ,  $SD_{age} = 4.15$ ,  $M_{education} = 17.57$ ,  $SD_{education} = 1.75$ ,  $N_{females} = 14$ ) and 29 older adults ( $M_{age} = 66.03$ ,  $SD_{age} = 6.83$ ,  $M_{education} = 15.79$ ,  $SD_{education} = 1.82$ ,  $N_{females} = 17$ ).

For inclusion in the study, participants were required to be novice video game players, right handed, have normal or corrected vision, no history of major medical or psychological illnesses, and MRI compatible. Older adults were required to score a minimum of a 26 on the

Mini-Mental Status Examination (MMSE; Folstein et al., 1975) to exclude participants with possible dementia. Participants signed an informed consent approved by the University of Texas Southwestern Medical Center and the University of Texas at Dallas Institution Review Boards. Compensation included \$40/hr for an imaging session and \$10/hr for a behavioral session.

### 2.2.2. Behavioral Learning Methods

Video games have been used as effective tools for cognitive training in both younger and older adults, primarily due to their engaging nature and ecological realism (Anguera et al., 2013; Basak et al., 2008; Boot et al., 2010b; Glass, Maddox, & Love, 2013; Green & Bavelier, 2006; Li, Chen, & Chen, 2016). The current study chose to investigate how a participant's ability to learn two different short video games, referred to as casual games, are related to task-based functional connectivity. These casual games are the current measures of complex tasks.

Game play was conducted on networked PC computers with 22'' Dell P2213 monitors, which were set at a 60Hz with 1920\*1080 resolution. Game inputs were made using the computer mouse. The current study used two casual games -- Tank Attack 3D (action game) and Sushi-Go-Round (strategy game) -- from a free gaming website that has been used in previous studies on casual video games ([www.miniclips.com](http://www.miniclips.com), Baniqued et al., 2012, 2013). The participants played both games, each for 75 minutes, with 15 minutes added for older adults to reduce age-related fatigue effects. Game order was counterbalanced across participants. Both games contained varying levels of difficulty that were adaptive based on the participant's performance. It is important to note that both Tank Attack 3D and Sushi-Go-Round required some degree of cognitive control.

In Tank Attack 3D, a game comparable to those previously found to relate to tasks of perceptual speed, and thus defined as an action-based game, participants were required to control the shooting of an automatically running tank. Participants had to discriminate between enemy and civilian targets, while shooting enemy buildings and units before the end of 5.5 minutes. This game required cognitive control mechanisms of inhibition and task-switching to successfully perform the game. In Sushi-Go-Round, a game found to relate to tasks of working memory and reasoning, and thus defined as a strategy-based game, participants were required to create and serve sushi to customers. Participants had to achieve a specific monetary goal for each level, while memorizing and recalling sushi recipes, cleaning tables, and ordering supplies before the end of 6 minutes of game duration. Mechanisms of goal-maintenance, switching, long-term memory, and updating had to be utilized in order to successfully perform Sushi-Go-Round. Younger adults completed an average of 11.44 games for Tank Attack 3D ( $SD_{tank} = 1.13$ ) and 11.41 games for Sushi-Go-Round ( $SD_{sushi} = 1.21$ ). Older adults completed an average of 14.79 games for Tank Attack 3D ( $SD_{tank} = 3.33$ ) and 16.89 games for Sushi-Go-Round ( $SD_{sushi} = 2.15$ ). Older adults played more games due to more losses; the total play time for lost games was shorter.

A learning rate for each participant was calculated based on a logarithm function ( $y=b*\ln(x)+a$ ). This function was fit to the total score across all games the participant played. The slope (b) of the logarithmic function was used as an indicator of participant learning, with a higher slope parameter indicating faster learning of the game. Learning rates have previously been calculated with similar protocol in studies using experimental video games (Boot et al., 2010), commercial video games (Basak et al., 2008; Ray et al., 2017), and working memory

tasks (Basak & O'Connell, 2016). Therefore, individual learning rates for both Tank Attack 3D and Sushi-Go-Round were calculated for all 52 participants.

### 2.2.3. Scanning Procedure and Analyses

Anatomical and functional images were collected during a 45-minute scanning session. Functional images were obtained from two in-scanner tasks; these tasks were subdivided to indicate our three levels of varying cognitive control components in the current study. Both the Task Switch paradigm and Memory Updating paradigm used a hybrid block and event-related design (Braver, Reynolds, & Donaldson, 2003; Nashiro, Qin, O'Connell, & Basak, 2018), however for the current functional connectivity analysis we only used the block design. The tasks were programmed in E-prime 2.0 software (Psychology Software Tools, Pittsburgh, PA).

#### 2.2.3.1. Scanner Tasks

The Task Switch paradigm consisted of alternating blocks of rest and task (Braver et al., 2003; Nashiro et al., 2018). Each task block included 30 trials, where the stimuli was presented for 3 s. A jittered fixation interval of 1, 3, or 5 s separated stimuli presentation. Thus, the duration of task blocks were 154 s and rest blocks were 30 s. During the task, participants were presented with a single digit on a blue or pink background; the color background indicated the specific task that participants were performing during that trial. The digits ranged from one to nine, excluding the number five. A blue colored background required participants to indicate whether the number presented on the screen was higher or lower than the number five, hence why the number five was never presented during the Task Switch paradigm. The pink background required participants to indicate whether the number presented on the screen was odd or even. A left button-box press indicated a lower/odd judgement; a right button-box press

indicated a higher/even judgment, depending on the probed task. To remove memory demand, task-related decision rules were presented in the bottom corners of the screen (i.e., bottom left – lower/odd; bottom right – higher/even). Participants first completed two Single task blocks, specifically, a block of only blue trials, followed by a block of only pink trials. The last two blocks consisted of alternating trials of blue and pink; this is the Dual task condition. Although these trials randomly alternated between blue and pink trials, half of the trials were non-switch trials, in which the previous trial required the same task rules (e.g., pink followed by pink) and the other half of the trials were switch trials, in which the previous trial required different task rules than the current trial (e.g., pink followed by blue). The Single task required limited cognitive control components, relying solely upon task maintenance. The Dual task relied upon components of both rule maintenance and unpredictable switch mechanisms.

The second in-scanner task, the Memory Updating paradigm, is similar to previously used unpredictable 2-back tasks (Basak & Verhaeghen, 2011a; Oberauer, 2005). This task required three components of cognitive control for task performance: maintenance, unpredictable switching, and updating. Participants completed two runs of alternating 30 s blocks of rest and task, resulting in a total of eight rest blocks and six task blocks for each run. Each task block contained 20 trials, in which a digit was presented for 1450 ms. A 50 ms inter-trial interval separated each digit. Digits were presented in either pink or yellow colored-font, participants were instructed to indicate whether the current digit (e.g., pink 8), in a particular color, was the same or different from the previous digit presented in the same color (e.g., pink 6). The left button box indicated a same judgement; the right button box indicated a different judgement. Switch components were required when the digit changed from pink to yellow, or vice versa. In

contrast, update components were required when a particular color changed numeric value from the previous trial presented in that color. The task included an equal number of switch and non-switch trials and an equal number of update and non-update trials. Therefore, the Memory Updating task required three components of cognitive control: maintenance, unpredictable switching, and updating. Although the implemented Memory Updating task is similar to the N-back paradigm, the unpredictability of the switch expectancies have previously been shown to be more complex and cognitively demanding than the typical predictable version (Basak & O'Connell, 2016; Basak & Verhaeghen, 2011a).

All three tasks were verbal in nature and implemented color as a cue for switch demands. For instance, in the Dual task, two successive trials of the same color background indicated a non-switch condition. In Memory Updating, two successive trials of the same color numbers also indicated a non-switch condition. The final analysis consisted of task blocks accumulating to 60 trials for Single task, 60 trials for Dual task, and 240 trials for Memory Updating.

#### 2.2.3.2. fMRI Data Acquisition, Image Preprocessing, and Connectivity Analysis

Imaging was performed on a Philips Achieva 3T scanner (Philips Medical Systems, Andover, MA, USA) using a 32-channel head coil. The anatomical images were acquired with a transverse MPRAGE T1-weighted sequence (160 slices; TR = 8.1 ms; TE = 3.7 ms; flip angle = 12°; 256 x 204 mm FOV, voxel size = 1 mm<sup>3</sup>). Functional images during the Task Switch paradigm were acquired with an echo-planar sequence (39 slices; TR = 2000 ms; TE = 30 ms; flip angle = 70°; 64 x 64 mm FOV, voxel size = 3.44 x 3.44 x 4 mm). An echo-planar sequence was also used for acquisition during the Memory Updating paradigm (29 slices; TR = 1500 ms;

TE = 30 ms; flip angle = 60°; 64 x 64 mm FOV, voxel size = 3.44 x 3.44 x 5 mm). The first six EPI volumes were not recorded to allow the signal to reach steady-state magnetism.

Data was preprocessed using SPM12 (<http://fil.ion.ucl.ac.uk/spm/software/spm12/>). Anatomical images were normalized and segmented into white matter, gray matter, and cerebral spinal fluid masks. An artifact detection tool (ART) was used for motion correction, resulting in global mean and motion outliers ([http://www.nitrc.org/project/artifact\\_detec/](http://www.nitrc.org/project/artifact_detec/)). Functional images were subject to motion and slice-timed correction, realigned to the first volume using a six-parameter rigid body transformation, normalized to a study-specific template, and smoothed with a 6 mm full width at half-maximum (FWHM) Gaussian kernel. The study-specific template was created by averaging the smoothed images from an equal number (20 per group) of older and younger adult's high-resolution structural images, which were registered to the standard 152 T1 MNI template.

The methodological approach for functional connectivity was seed-to-voxel connectivity. The functional connectivity analyses were conducted using the *Conn* functional connectivity toolbox v16 (Whitfield-Gabrieli & Nieto-Castanon, 2012). *Conn* implements CompCor, a noise reduction method that extracts principal components from white matter and CSF time series (Behzadi, Restom, Liao, & Liu, 2007). Furthermore, the main effect of task blocks, scrubbing parameters, and six realignment parameters were used to remove confounds of noise. A band-pass high-filtering frequency of .008 Hz (e.g., 128 s high pass filter) was implemented to remove potential crosstalk of BOLD signals between blocks, but still filtering to enhance the signal to noise ratio for task-related data. First-level general linear models for the conducted seed-to-voxel analyses included two individual regressors: realignment parameters and motion artifact

parameters, specifically the global mean signal intensity and motion extracted using ART.

Bivariate correlation maps were created between the mean BOLD time series for each seed and mean BOLD time series for all other voxels in the brain for the task > rest contrasts. A Fisher Z transformation was applied to convert our bivariate correlations to group level connectivity patterns.

Two networks were chosen to investigate the relationship between casual game learning and task-related functional connectivity during tasks with varying cognitive control components: the cingulo-opercular network (CO) and fronto-parietal network (FP). For seed-to-voxel connectivity, a seed is defined as the average time series within the selected region of interest, this is correlated to the time series of all other voxels in the brain. Seed selection was driven by graph theory connectivity results (Power et al., 2011; Spreng, Sepulcre, Turner, Stevens, & Schacter, 2013), due to good correspondence between functional systems, defined via task-related fMRI and PET scans, and areal and modified voxel-wise graphs related to these functional systems (Power et al., 2011). After an initial selection of network seed locations from Power et al. (2011), this was further constrained to two seeds per network using limited betweenness centrality (Spreng et al., 2013) in order to limit the overlap between the functional systems for our chosen seeds. The two seed locations for each network were selected from Power et al. (2011). The cingulo-opercular network seeds were the dorsal anterior cingulate cortex (dACC: MNI -1, 10, 46) and left anterior insula/frontal operculum (aI/fO: MNI -35, 14, 5). The cingulo-opercular network has been defined as having two sub-graphs: task control (Dosenbach et al., 2007) and salience (Seeley et al., 2007). The seed regions for the current analyses are functionally related to task control. The fronto-parietal network seeds were the right dorsal

lateral prefrontal cortex (dlPFC: MNI 46, 28, 31) and the right frontal gyrus (frontal: MNI 44 8 34).

The first set of analyses investigated the task > rest functional connectivity maps for the attentional networks (CO and FP) during the Single task, Dual task, and Memory Updating conditions. Furthermore, action and strategy game learning rates were used as separate independent variables in the general linear model to evaluate the network correlations with respect to learning of a specific game type. Standardized scores for age and total gray matter volume were entered as continuous regressors to control for the effects of neurocognitive aging. There was a significant correlation between age and total gray matter volume ( $r = -.60, p < .001$ ). The second set of analyses were run to investigate the age-related differences in the relationship between game learning and functional connectivity of the attentional networks during the three different task complexities (task > rest). Younger > older and older > younger contrasts were run for this purpose.

Although a less common practice, the decision to investigate functional connectivity in task > rest contrasts was driven by previous findings (Fair et al., 2007; Fox, Snyder, Zacks, & Raichle, 2006). Fair et al. and Fox et al. investigated the use of block-designed fMRI tasks to measure resting state connectivity, finding that activity from task-blocks was linearly added on top of persistent spontaneous baseline activity involved in rest blocks. Thus, in tasks that interleave task and rest blocks, a contrast of rest > block gave the experimenters a more or less continuous state of the resting behavior the experimenters were interested in (Fair et al., 2007). Since the current study is interested in the relationship between game-learning external to the scanner and functional connectivity during tasks of varying cognitive control components, we

have investigated a similar, albeit opposite, contrast, task > rest, for all three tasks. This approach was taken to remove the persistent activity related to rest blocks.

The atlas-defined location of the peak voxel for some of the resulting clusters differed from the atlas-defined location of the majority of the voxels in that cluster. The tables of results will include two cluster locations if these identities differ. The first location on the table indicates the site of the peak voxel (indicated by a ‘+’), and the second location indicates the site of the majority of the voxels in the cluster (indicated by a ‘\*’). To identify whether these clusters were within-network or between-network, the larger corpus of network nodes by Power et al. (2011) were used to define the network of the resulting clusters. Four mm seeds from Power et al. (2011) MNI coordinates were created for the networks of investigation. This resulted in 14 seeds for the cingulo-opercular network and 25 seeds for the fronto-parietal network. Visual comparisons of our resulting clusters to the regions from previous network analyses were made by overlaying these network seeds on the resulting *t*-maps. CO seeds are colored in yellow and FP in green; furthermore, for the particular network that the seeds under investigation (in these seed-to-voxel analyses) belong, the Power et al. nodes are shown in black (e.g., for the dACC seed-to-voxel results, the Power et al. seeds for the CO network are colored in black).

### 2.3. Results

Behavioral results and the complexity relationship with task-related functional connectivity using these same 52 participants has previously been published in O’Connell and Basak (2018), in which the effect of task complexity was investigated across three networks (CO, FP, and additionally the default mode network) and two age groups. The current analyses include the added variable of learning rate in two causal games for a novel approach to

investigate the relationship between learning complex tasks and functional connectivity during tasks with varying cognitive control demands.

All functional connectivity analyses were corrected for multiple comparisons using cluster *p-FWE* at a *p*-value of .05 and a *p*-uncorrected voxel threshold at a *p*-value of .001 (Friston, Worsley, Frackowiak, Mazziotta, & Evans, 1994). The xjView toolbox (<http://www.alivelearn.net/xjview>) was used to localize peak voxels in significant clusters. The authors realize that the peak voxel and the majority of voxels in a significant cluster may differ in their localized region, therefore both are identified.

### 2.3.1. Game Learning, Task Complexity and Functional Connectivity

#### 2.3.1.1. Action Game Learning

For the Single task > Rest contrast, after controlling for age and gray matter volume, learning in the action game was related to functional connectivity of the dACC seed of the CO network to two clusters of voxels in the left and right precentral gyrus. According to the Power et al. (2011) seeds, these clusters are within the same CO network (see Table 3.1 and Figure 3.1). Connectivity for the FP seeds were not significantly related to learning of the action game during the Single task. For the moderately complex task (Dual task > Rest contrast), action game learning was only related to seeds from the FP network. The right dIPFC seed was significantly connected within-network to a cluster in the left middle frontal gyrus, whereas the right frontal seed was significantly connected to a cluster in the left superior frontal gyrus, a region visually identified as being part of the default mode network using the Power et al. (2011) seeds (see Figure 3.1). For the Memory Updating > Rest contrast, action game learning was not related to functional connectivity for seeds from either of the attentional networks.

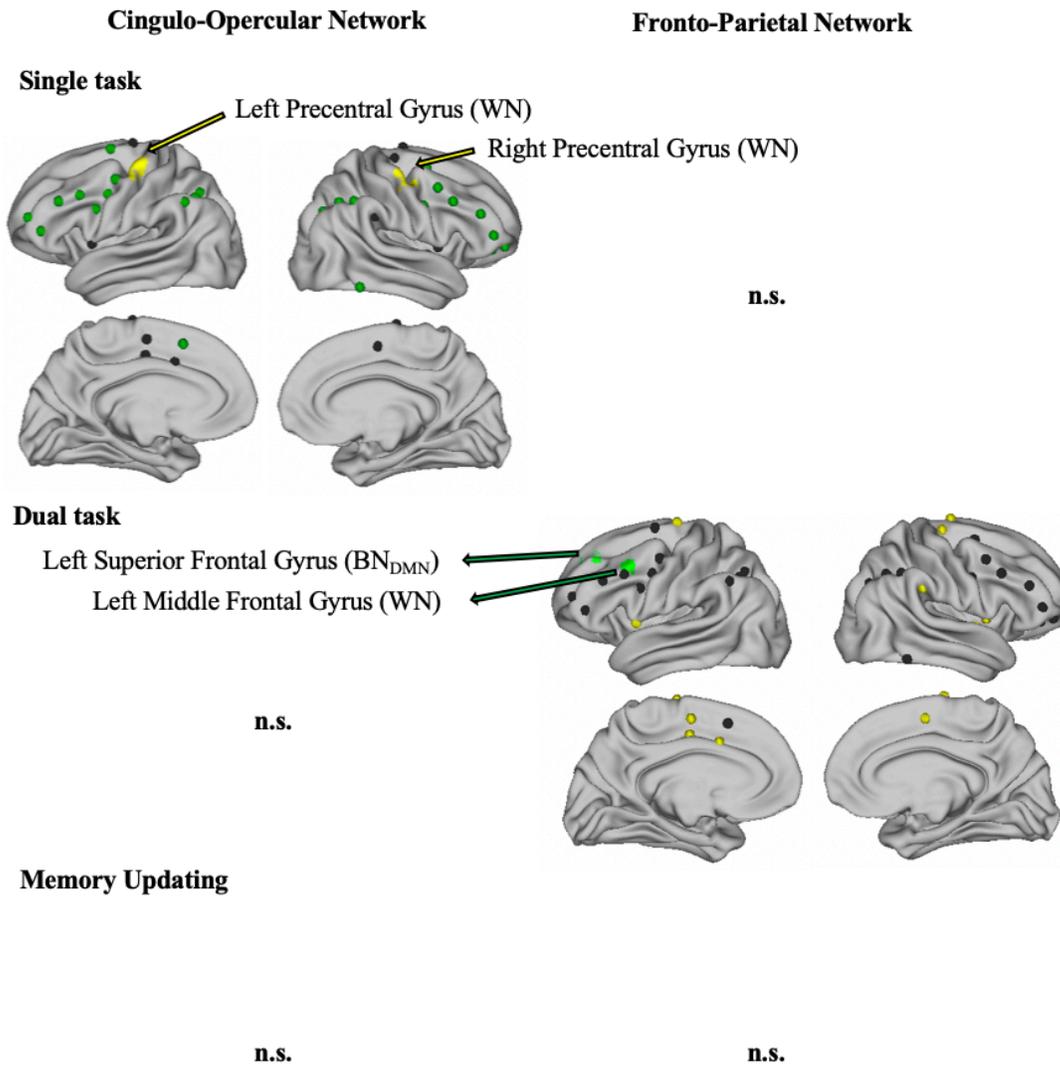


Figure 3.1. Significant  $t$ -maps for Task Complexity (task > rest) across the two attentional networks, controlling for age and total gray matter volume, predicted by action game learning. Multiple seed-to-voxel general linear models (GLM) were conducted across three tasks (Single task > Rest, Dual task > Rest, and Memory Updating > Rest) and two networks (CO and FP). The color of significant clusters indicates the network of seed selection for the analysis: CO (yellow) and FP (green). The resulting maps from the task > rest contrasts are overlaid on Power et al. (2011) network seeds to differentiate between within- and between-network connectivity. For the seed-to-voxel connectivity maps of a particular network (e.g., CO), the Power et al. seeds for that particular network are displayed in black and the other network is displayed in its respective color.

### 2.3.1.2. Strategy Game Learning

For the Single task > Rest contrast, after controlling for age and gray matter volume, learning in the strategy game was limited to one seed and one cluster, with the left anterior insula of the CO network connected to the left inferior parietal lobe (IPL) of the default mode network (see Table 3.1 and Figure 3.2). Although the IPL varies in network identity depending on location, this particular cluster is found to be closer to the angular gyrus, and is identified as belonging to the default mode network (Grady et al., 2010). For the moderately complex task (Dual task > Rest contrast), strategy game learning was not related to functional connectivity for seeds from either of the attentional networks. However, for the Memory Updating > Rest contrast, strategy game learning was related to functional connectivity for one of the seeds from both attentional networks. The dACC seed of the CO network was significantly correlated to clusters within-network and between-network to the FP, motor, and DM networks. Specifically, the dACC seed was significantly correlated within-network to the right precuneus and right precentral gyrus, and between network to the left inferior temporal gyrus of the DM network, the left postcentral gyrus of a motor network, and the left inferior frontal gyrus for the FP network. The right frontal seed of the FP network was significantly correlated to clusters in the right precuneus, left superior frontal gyrus, and middle orbitofrontal gyrus. According to the Power et al. (2011) seeds, all of these clusters are located in the DM network.

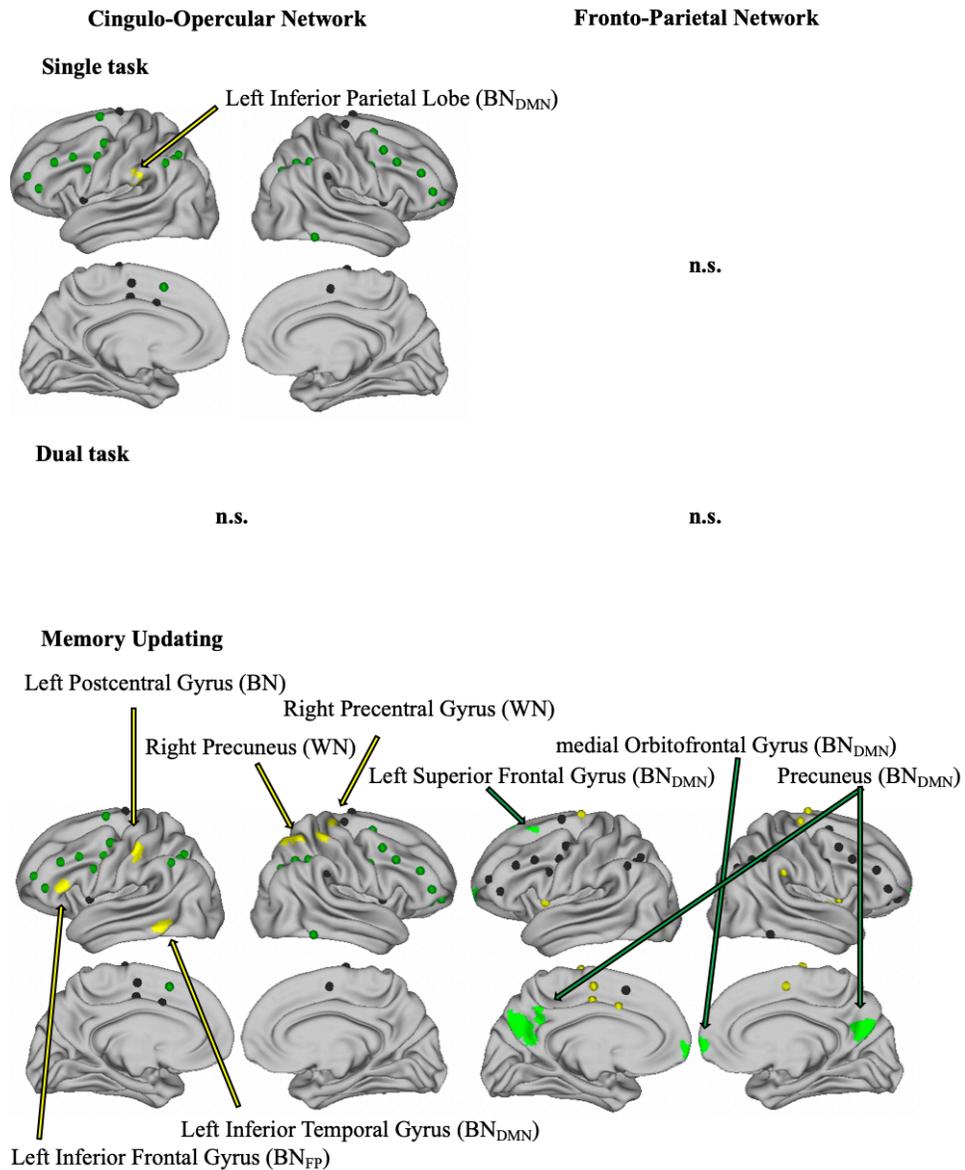


Figure 3.2. Significant  $t$ -maps for Task Complexity (task > rest) across the two attentional networks, controlling for age and total gray matter volume, predicted by strategy game learning. Multiple seed-to-voxel general linear models (GLM) were conducted across three tasks (Single task > Rest, Dual task > Rest, and Memory Updating > Rest) and two networks (CO and FP). The color of significant clusters indicates the network of seed selection for the analysis: CO (yellow) and FP (green). The resulting maps from the task > rest contrasts are overlaid on Power et al. (2011) network seeds to differentiate between within- and between-network connectivity. For the seed-to-voxel connectivity maps of a particular network (e.g., CO), the Power et al. seeds for that particular network are displayed in black and the other network is displayed in its respective color.

Table 3.1. Seed-to-voxel statistical map summary predicted by learning in novel casual games (either action or strategy) during three tasks (Single task > Rest, Dual task > Rest, and Memory Updating>Rest), for the two attentional networks (CO and FP). These general linear models controlled for age and total gray matter volume and resulted in significant clusters surpassing a *p-FWE* corrected *p*-value of .05.

<b>Single Task</b>							
<b>Action Game Learning</b>							
		<b>B</b>				<b>no. of</b>	<b>t-</b>
<b>CO</b>		<b>A</b>	<b>x</b>	<b>y</b>	<b>z</b>	<b>voxels</b>	<b>value</b>
dACC							
	left	Precentral Gyrus	-40	-10	64	121	5.49
	right	Precentral Gyrus	50	0	50	94	5.39
left anterior Insula							
--							
<b>FP</b>							
right Frontal							
--							
right dlPFC							
--							
<b>Strategy Game Learning</b>							
<b>CO</b>							
dACC							
--							
left anterior Insula							
	left	Inferior Parietal Lobe, Parietal Operculum Cortex	-56	-28	26	109	5.7
<b>FP</b>							
right Frontal							
--							
right dlPFC							
--							
<b>Dual Task</b>							
<b>Action Game Learning</b>							
<b>CO</b>							
dACC							
--							
left anterior Insula							
--							
<b>FP</b>							
right Frontal							
	left	Superior Frontal Gyrus, Frontal Pole	-20	48	38	76	5.76
right dlPFC							
	left	Middle Frontal Gyrus	9	-46	26	38	4.74
<b>Strategy Game Learning</b>							
<b>CO</b>							
dACC							
--							
left anterior Insula							
--							
<b>FP</b>							
right Frontal							
--							

right dlPFC	--						
<b>Memory Updating Action Game Learning</b>							
<b>CO</b>							
dACC	--						
left anterior Insula	--						
<b>FP</b>							
right Frontal	--						
right dlPFC	--						
<b>Strategy Game Learning</b>							
<b>CO</b>							
dACC							
right	Precuneus, Superior Parietal Lobe	22	-64	70	220	6.14	
left	Inferior Temporal Gyrus, Middle Temporal Gyrus	-54	-50	-10	94	5.08	
left	Postcentral Gyrus	1	-56	-20	82	4.89	
right	Precentral Gyrus	34	-16	70	74	4.63	
left	Inferior Frontal Gyrus	-54	32	4	73	5.24	
left anterior Insula	--						
<b>FP</b>							
right Frontal							
right	Precuneus, Precentral Gyrus	7	6	-64	32	539	5.89
left	Superior Frontal Gyrus	9	-14	48	52	157	5.81
right	medial Orbitofrontal Gyrus, Frontal Pole	11	6	64	-12	126	6.85
right dlPFC	--						

### 2.3.2. Game Learning, Task Complexity and Functional Connectivity: Age Differences

Although we analyzed a broad age range of participants, the first set of results were acquired with age and gray matter removed in order to investigate the overall pattern of functional connectivity in relation to game learning across three levels of task complexity. We must acknowledge that these results may differ between older and younger adults, since network connectivity changes with age. Therefore, it is interesting and necessary to investigate the differences between our older and younger adult participants in the relationship between task-related functional connectivity and complex task learning in the attentional networks. Thus, we

directly investigated the specific seeds and tasks where younger adults had greater connectivity than older adults (younger > older) and where older adults had greater connectivity than younger adults (older > younger).

#### 2.3.2.1. Action Game Learning

For the Single task > Rest contrast, action game learning in both age-related contrasts were related to CO seed connectivity to regions with limited functional consequence. For instance, for the younger > older contrast, the dACC was correlated to the left lateral ventricle and for the older > younger contrast, the left anterior insula was correlated to a left extra-nuclear cluster (see Table 3.2). For the Dual task > Rest contrast, action game learning was related to greater functional connectivity for younger adults, in comparison to older adults, for the left anterior insula seed of the CO to the right IPL of the FP network and connectivity of the right frontal seed of the FP to the right IPL of the DM network and the right inferior frontal gyrus of the CO network (see Table 3.2 and Figure 3.3). In contrast, action game learning was related to greater within-network function connectivity for older adults, in comparison to younger adults, for the right dlPFC seed of the FP network to the right middle frontal gyrus. For the Memory Updating > Rest contrast, action game learning was related to greater between-network connectivity for younger adults, in comparison to older adults, for the right dlPFC seed of the FP to the left superior temporal gyrus of the DM network. Action game learning was related to greater within-network connectivity for older adults, in comparison to younger adults, for the dACC seed of the CO network to the left precentral gyrus.

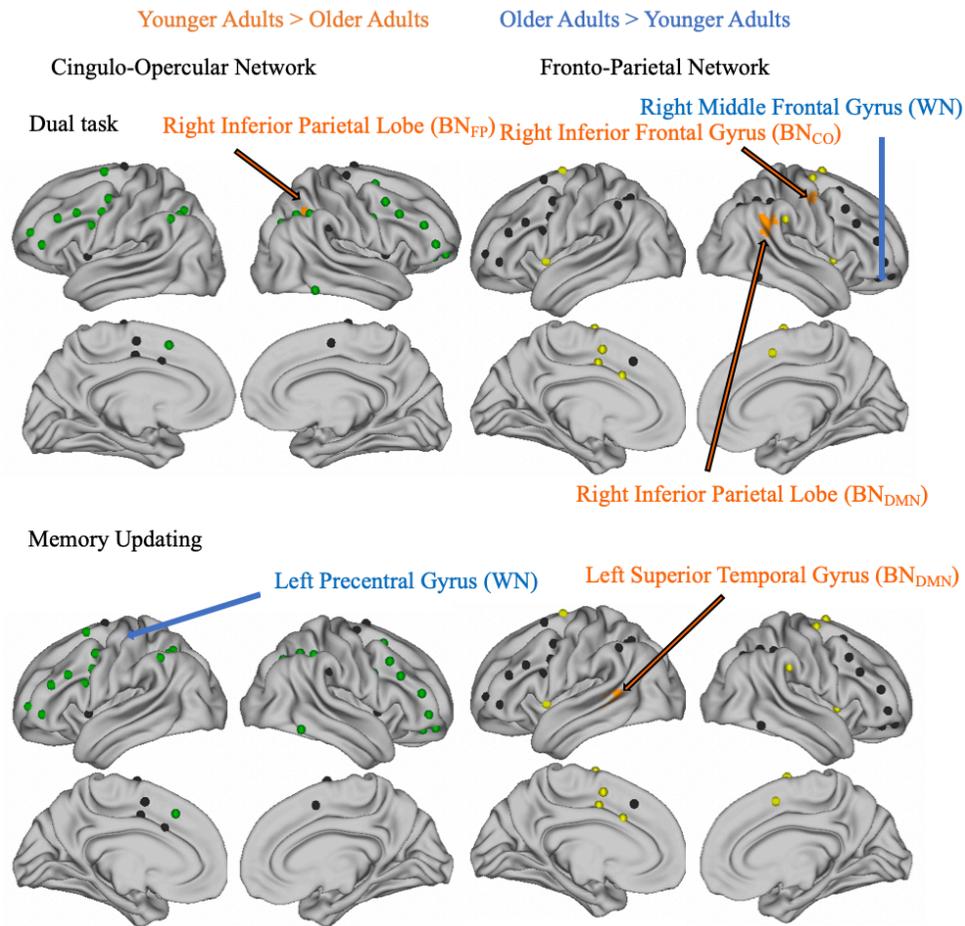


Figure 3.3. Age-related differences in significant t-maps for Task Complexity (task > rest) across the attentional networks, predicted by action game learning. Multiple seed-to-voxel general linear models (GLM) were conducted across three tasks (Single task > Rest, Dual task > Rest, and Memory Updating > Rest) and two networks (CO and FP) for two separate contrasts: younger > older (YA > OA) and older > younger (OA > YA).

#### 2.3.2.2. Strategy Game Learning

Strategy game learning was not significantly related to functional connectivity during any of the three tasks or either of the attentional networks for the older > younger contrast. Strategy game learning was also not significantly related to functional connectivity for the Single task > Rest contrast for seeds from the attentional networks for the younger > older contrast. However, younger adults did result in greater connectivity, in relation to strategy game learning, for the

Dual task > Rest contrast for the dACC seed of the CO network, which was significantly connected to the right pallidum and within-network to the left precentral gyrus (see Table 3.2 and Figure 3.4). For the Memory Updating > Rest contrast, strategy game learning was related to greater connectivity for younger adults, in comparison to older adults, for the left anterior insula seed of the CO network to the left superior parietal lobe of the FP network and connectivity for the right dlPFC seed of the FP network to the left middle temporal gyrus of the DM network.

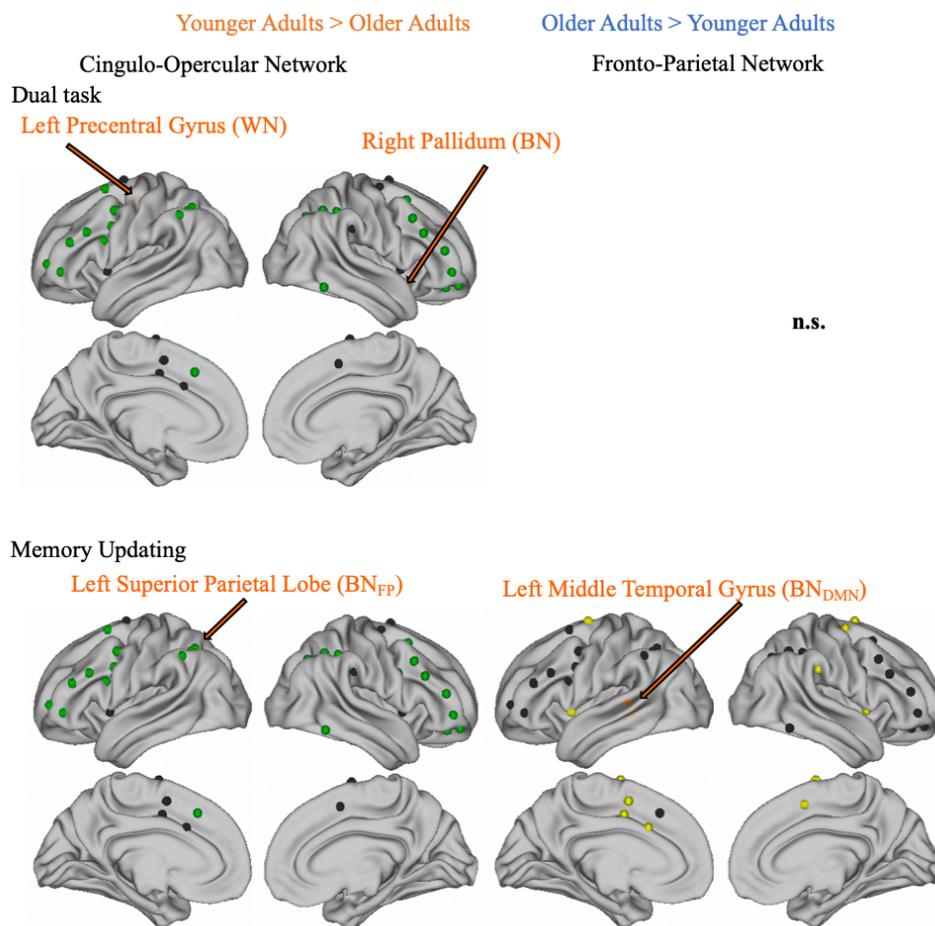


Figure 3.4. Age-related differences in significant t-maps for Task Complexity (task > rest) across the attentional networks, predicted by strategy game learning. Multiple seed-to-voxel general linear models (GLM) were conducted across three tasks (Single task > Rest, Dual task > Rest, and Memory Updating > Rest) and two networks (CO and FP) for two separate contrasts: younger > older (YA > OA) and older > younger (OA > YA).

Table 3.2. Seed-to-voxel statistical map summary for age-related differences predicted by learning in novel casual games (either action or strategy) during three tasks (Single task > Rest, Dual task > Rest, and Memory Updating>Rest), for the two attentional networks (CO and FP) for younger > older and older > younger contrasts. These general linear models controlled for age and total gray matter volume and resulted in significant clusters surpassing a *p-FWE* corrected *p*-value of .05.

<b>Single Task</b>						
<b>Action Game Learning</b>						
<b>CO</b>	<b>BA</b>	<b>x</b>	<b>y</b>	<b>z</b>	<b>no. of voxels</b>	<b>t-value</b>
dACC						
<i>Younger &gt; Older</i>						
left Lateral Ventricle, Thalamus		-18	-30	20	72	6.3
<i>Older &gt; Younger</i>						
--						
left anterior Insula						
<i>Younger &gt; Older</i>						
--						
<i>Older &gt; Younger</i>						
left Extra-Nuclear		-28	-10	28	83	6.27
<hr/>						
<b>FP</b>						
right Frontal						
<i>Younger &gt; Older</i>						
--						
<i>Older &gt; Younger</i>						
--						
right dlPFC						
<i>Younger &gt; Older</i>						
--						
<i>Older &gt; Younger</i>						
--						
<hr/>						
<b>Strategy Game Learning</b>						
<hr/>						
<b>CO</b>						
dACC						
<i>Younger &gt; Older</i>						
--						
<i>Older &gt; Younger</i>						
--						
left anterior Insula						
<i>Younger &gt; Older</i>						
--						
<i>Older &gt; Younger</i>						
--						
<hr/>						
<b>FP</b>						
right Frontal						
<i>Younger &gt; Older</i>						
--						
<i>Older &gt; Younger</i>						
--						
right dlPFC						

*Younger > Older*

--

*Older > Younger*

--

---

**Dual Task  
Action Game Learning**

---

**CO**

dACC

*Younger > Older*

--

*Older > Younger*

--

left anterior Insula

*Younger > Older*

right Inferior Parietal Lobe, Superior Parietal Lobe 36 -48 46 94 4.68

*Older > Younger*

--

---

**FP**

right Frontal

*Younger > Older*

right Inferior Parietal Lobe, Angular Gyrus 52 -44 24 259 6.76

right Inferior Frontal Gyrus, Precentral Gyrus 52 -14 60 76 4.8

*Older > Younger*

--

right dlPFC

*Younger > Older*

--

*Older > Younger*

right Middle Frontal Gyrus, Frontal Pole 28 50 20 77 6.24

---

**Strategy Game Learning**

---

**CO**

dACC

*Younger > Older*

right Pallidum 22 -10 -4 67 5.58

left Precentral Gyrus -34 -20 54 66 4.98

*Older > Younger*

--

left anterior Insula

*Younger > Older*

--

*Older > Younger*

--

---

**FP**

right Frontal

*Younger > Older*

--

*Older > Younger*

--

right dlPFC

*Younger > Older*

--

Older > Younger

--

---

**Memory Updating  
Action Game Learning**

---

**CO**

---

dACC

Younger > Older

--

Older > Younger

left Precentral Gyrus

4 -22 -30 64 203 5.31

left anterior Insula

Younger > Older

--

Older > Younger

--

---

**FP**

---

right Frontal

Younger > Older

--

Older > Younger

--

right dlPFC

Younger > Older

left Superior Temporal Gyrus, Middle Temporal Gyrus

-56 -40 4 114 5.2

Older > Younger

--

---

**Strategy Game Learning**

---

**CO**

---

dACC

Younger > Older

--

Older > Younger

--

left anterior Insula

Younger > Older

left Superior Parietal Lobe, Lateral Occipital Gyrus

7 -24 -72 50 114 5.34

Older > Younger

--

---

**FP**

---

right Frontal

Younger > Older

--

Older > Younger

--

right dlPFC

Younger > Older

left Middle Temporal Gyrus, Superior Temporal Gyrus

22 -60 -38 2 76 4.76

Older > Younger

--

---

## 2.4. Discussion

Understanding what constitutes a good learner is often limited to the behavioral markers of an individual's strengths. In the current study we extended this understanding to include neural markers from good learners in multiple measures of complex tasks, by investigating whether learning rates in two different genres of causal video games differentially predicted connectivity of the attentional networks during three tasks with varying degrees of cognitive control. Our results identify the neural correlates recruited by good complex task learners during tasks with differing cognitive demands. One finding common between the two complex task results is the increase in the number of between-network correlations with an increase in task complexity. This suggests that when a task becomes more difficult, better learners will rely upon the coupling of multiple neural networks for task completion. However, our results indicate that this pattern of increased coupling differed by within-scanner task and extent of between-network connectivity for the two casual games. Better learners in the action game resulted in FP connectivity during the moderate task (Dual task), whereas better learners in the strategy game resulted in both CO and FP connectivity during the most complex task (Memory Updating). Regarding age-related differences, across both the moderate and most complex tasks, younger adults resulted in significantly more connectivity than older adults in relation to learning in both complex tasks. However, the relationship between action game learning and functional connectivity was compensatory for both younger and older adults, resulting in significant neural correlates associated with better learners in both age-groups. In contrast, the relationship between strategy game learning and functional connectivity was only compensatory for younger adults.

#### 2.4.1. Game Learning and Attentional Network Connectivity

The effect of casual game learning on the relationship between functional connectivity and task complexity resulted in different findings depending on the casual game genre learned, thus informing us about the video game itself. For instance, learning in Tank Attack 3D, that is the action video game, was related to within-network connectivity for the CO network during the Single task, but FP network connectivity during the task of moderate complexity (Dual task). Strategy game learning, however, significantly related to limited between-network connectivity for the CO seed to the DM network during the Single task, but robust within- and between-network connectivity for both attentional networks during the task with the most complexity (Memory Updating).

The FP network has previously been found to be vital for cue-response mapping adaptation and working memory performance (Dosenbach et al., 2007; Laird et al., 2011; O'Connell & Basak, 2018; Owen et al., 2005). The Dual task required both rule maintenance and unpredictable switching between two tasks; this is similar to the mechanisms necessary for performance of Tank Attack 3D. Tank Attack 3D is a relatively simple action-based video game, which relies upon inhibitory and attentional control mechanisms (e.g., switch dynamics). Therefore, all aspects of these findings align, e.g., significant FP network connectivity during a task with similar underlying switch mechanisms to the game itself. This same pattern is true for the strategy game and Memory Updating, both of which required unpredictable switching of attention. However, Memory Updating also includes the cognitive component of updating, which does not underlie the action game. This could be the reason for a lack of connectivity during Memory Updating for action game learning.

Strategy game learning significantly relates to both within- and between-network connectivity for both attentional networks during the task with the most complexity (Memory Updating). Sushi-Go-Round is a difficult, strategy-based game with underlying aspects of both cognitive control and long-term memory. Results indicate that learning in Sushi-Go-Round was related to broad connectivity of the CO network to regions both within-network and to regions of the FP and DM networks. In contrast, FP network connectivity was limited to regions of the DM network. Thus, better learners had more connectivity between the attentional network seeds to regions in the DM network.

Although less popular than the Default Mode Hypothesis (Buckner, Andrews-Hanna, & Schacter, 2008), a Cognitive Control Hypothesis suggests that a coupling of attentional network regions with default mode regions may indicate a cognitively complex task (O'Connell & Basak, 2018). For instance, DM network regions have been found to play a role in priming a reaction to unpredictable stimuli, which is related to the role of the FP network and includes cue-response adaptation and switch mechanisms (Dosenbach et al., 2007; Fransson, 2005; Greicius, Krasnow, Reiss, & Menon, 2003; Hahn, Ross, & Stein, 2007; Laird et al., 2011; Owen et al., 2005). The Memory Updating task required switching attention to the relevant memory target at unpredictable times (cued by the color of the digit) and was extremely cognitively demanding, which plausibly left very few resources for mind wandering (a primary theme of the Default Mode Hypothesis). These results are in line with research associating DM network activation to cognitive mechanisms underlying planning future behavior, mental search, semantic and episodic memory, and signaling environmental change (Fransson, 2005; Fransson & Marrelec, 2008; Greicius et al., 2003; Mayes & Cermak, 2000; Pearson, Heilbronner, Barack, Hayden, & Platt,

2011). Our between-network results suggest that individuals who rely on this cross-talk between the attentional networks and DM network for tasks with high cognitive control demands, are the same individuals who will learn a strategy game faster. Thus, the between-network coupling of the attentional and DM networks is effective for both learning and performing high-order cognition.

#### 2.4.2. Game Learning and Attentional Network Connectivity: Age Differences

The relationship between different types of complex tasks and attentional networks differ among older and younger adults. Across both the moderate and most complex tasks, younger adults resulted in significantly more connectivity than older adults. This is consistent with aging literature on functional connectivity (Andrews-Hanna et al., 2007; Campbell et al., 2012; Damoiseaux & Greicius, 2009; Geerligns, Renken, Saliassi, Maurits, & Lorist, 2015). Older adults did result in more within-network clusters in relation to action game learning, whereas the resulting clusters for younger adults were primarily between network, for both the Dual task and Memory Updating. The resulting clusters indicate compensatory correlates for both younger and older adults for the relationship between action game learning and functional connectivity during the moderate and most complex tasks. However, there were no significant increases in connectivity favoring older adults for the relationship between strategy game learning and functional connectivity of the attentional networks. Only the resulting clusters for younger adults indicate compensatory correlates for this relationship between strategy game learning and functional connectivity during the moderate and most complex tasks. The different patterns of significance suggest that the age of the learners influences the relationship between ability to learn complex tasks and connectivity for the attentional networks. For instance, better older adult

learners had more within-network connectivity compared to younger adults, whereas younger adults had more between-network connectivity. This suggestion that better younger adult learners rely upon between-network connectivity to complete the tasks. Whereas, better older adult learners rely upon within-network connectivity to complete the tasks.

To our knowledge, the current approach, which predicted task-related functional connectivity using learning rates, is novel. The results in the current study were able to indicate the connectivity patterns of good learners for the specific complex tasks and age-contrasts. These findings supplement our current understanding of neural markers of good learners during different cognitive states but can also translate to training studies. In using functional connectivity to understand the mechanisms underlying training procedures, researchers have the ability to create training methodologies that tap onto networks that are at risk of declining, specifically in older adults. The current results indicate that a complex attentional control task (e.g., Memory Updating) or a complex casual game (e.g., Sushi-Go-Round) are examples of such training paradigms. By increasing the corpus of literature surrounding specific aspects of functional connectivity and how they relate to cognitive processes, we can understand the basic dynamics of task-related network recruitment.

## CHAPTER 4

### GENERAL DISCUSSION AND CONCLUSION

#### 2.5. Overview

In the current dissertation we focused on how probe-cue expectancies and their underlying neuronal differences systematically effected transfer to complex tasks (Experiment 1) and how the neural correlates during tasks with unpredictable expectancies related to learning in complex tasks (Experiment 2). Probe-cue expectancy refers to the ability to predict the response, comparison, and/or location of the upcoming stimulus. For instance, in the typical N-back task, the probe-cue expectancy is set to the current N. Thus, the current stimulus is always compared to the stimulus N-positions prior. In the N-back task, usually the cue is initially indicated via instruction; it can, however, be presented via color, location, sound, etc. In Experiment 1, probe-cue was based on tree location, whereas in Experiment 2, probe-cue was based on color. When the order of location or color was stable (yellow, yellow, pink, pink, yellow, yellow, etc.), the participant could predict upcoming probes. When the order of location or color was variable (yellow, pink, pink, pink, yellow, pink, etc.), the participant could not predict upcoming probes. The neural differences in ability to anticipate future items has previously been found to differ (Braver & Cohen, 2000; Braver et al., 2007).

Proactive control, which biases an anticipatory response for to-be-attended items, involves sustained activation of the lateral PFC, which is regulated by phasic bursts of dopamine that are learned over the course of a task in order to enable the appropriate signals for updating and maintaining relevant task information (Braver et al., 2007). Reactive control, which is a stimulus driven response for to-be attended information and found in situations with high

probabilities of interfering information, involves transient activation of the lateral PFC, which is only evident when there are enough contextual representations for the relevant stimuli to be reactivated during retrieval. Association regions and sensory-specific regions are activated for this contextually-bonded information, along with activity in the anterior cingulate cortex. The anterior cingulate cortex underlies top-down control for interference resolution of the non-relevant task information that may be dominant or re-activated by these association regions (Braver et al., 2007). Inhibiting interfering information is pertinent for both proactive and reactive control. Proactive control mechanisms serve to direct attention to upcoming information and prevent interference. Reactive control mechanisms activate many items in the active store and detect and suppress the interfering items from retrieval. Specific task elements will promote preventative or suppressant inhibitory actions. In the current dissertation we intended to investigate whether probe cue expectancy is one example of these specific task elements.

Experiment 1 was intended to investigate whether training in a task that biases proactive or reactive control would result in significant transfer to tasks that the neural regions of the different control systems underlie, with specific interest in transfer to complex tasks. Experiment 2 was intended to investigate whether learning in complex tasks was related to neural correlates between any of these control regions and for regions within the attentional networks. These two experiments intended to understand the relationship between working memory and complex tasks, but more specifically, how probe-cue expectancy relates to this relationship. Two methodological approaches were used to investigate this, 1) a behavioral training, to examine *how* probe-cue expectancies in working memory and complex tasks are related and 2) functional connectivity, to examine *why* unpredictable probe-cue expectancies in working memory and

complex tasks are related. Both studies suggest a strong relationship between working memory and complex tasks; however, it is important to note that both studies have experimental limitations and suggest necessary future studies to expand the current findings and theories.

#### 4.2 Summary of results and interpretation

Experiment 1 implemented a randomized control training comparing transfer across three groups: a predictable expectancies working memory updating group, an unpredictable expectancies working memory updating group, and a control group. The working memory trainings were individualized adaptive, had a maximum set-size (N) of 12, provided feedback, and included a gamified environmental array. Our results found significant transfer to a complex task composite for both training groups, in comparison to the control group. We also found that both training groups resulted in significant transfer to constructs of inhibition and episodic memory, in comparison to the control group. These findings do not benefit one working memory training group over the other. Although a key goal of the first experiment was to elucidate the control mechanisms used in predictable and unpredictable working memory tasks, we failed to meet this goal with our primary hypothesis analyses. However, exploratory analyses investigating individual differences did insinuate that one training was more beneficial to not only high performers, but also low performers in the training task itself. Our results using performance-based grouping variables bifurcated the pattern of transfer to suggest an effect favoring training in unpredictable probe-cue expectancies, particularly for individuals with initially high performance in the trained task and those better at learning the trained task. Furthermore, our individual differences analyses suggest a benefit to the inhibition construct for the unpredictable expectancies training group, compared to the control group, when initial

performance in the trained task was used as a grouping variable, regardless of whether the participants were initially high or low in their performance. The number of participants in each group based on performance is quite low, however, we suggest that these findings tell us the best strategy for working memory training to use in individuals with working memory deficits. In particular, we suggest that unpredictable expectancies training will be the most beneficial for older adults, as found in Basak and O'Connell (2016), or for children.

A key goal of the second study was to investigate the relationship between unpredictable probe-cue expectancies and complex tasks using functional connectivity. Varying the degree of cognitive control components during the within-scanner tasks tested whether learning in out-of-scanner complex tasks differentially predicted functional connectivity of the attentional networks in tasks with different degrees of cognitive control. Two of these tasks included unpredictable switch mechanisms. Importantly, the most difficult within-scanner task in Experiment 2 was the modified unpredictable N-back task, which was similar to the unpredictable expectancies training task implemented in Experiment 1, however, with a set memory load of  $N=2$ . The relationship between learning in either a strategy game, with multitasking, working memory, and long-term memory elements, or an action game, with task switching and perceptual speed elements, and functional connectivity during the three tasks suggests that not only will type of complex task change the neural correlates, but the correlates will be cognitive mechanism specific.

The regions defined by Braver and colleagues (2007) as crucial for inhibitory responses and cue retrieval are the same regions that were found to be neural correlates of the strategy game during the unpredictable working memory updating task. For instance, the dorsal anterior

cingulate cortex (dACC) was a seed selected from the cingulo-opercular (CO) network (Power et al., 2011). This region is also highlighted by Braver et al. (2007) as necessary in inhibitory responses for interfering information. The dACC was significantly correlated with regions within the CO network and to regions of the fronto-parietal (FP) network in relation to learning in the strategy game, but only during this unpredictable working memory updating task. The CO and FP are attentional networks believed to differ regarding stable task activation (CO) and flexible task activation (FP) to support working memory and cognitive control (Dosenbach et al., 2007; Laird et al., 2011; Owen et al., 2005). Our results suggest that better learners in a complex task rely upon these between-network communications to perform a task with unpredictable probe-cue expectancies. This fact, paired with significant correlates between the attentional network seeds and regions of the default mode (DM) network, suggest that better learners in complex tasks rely upon the same neural mechanisms of reactive control to perform the task with unpredictable probe-cue expectancies.

The DM network is often cited as involved in task-irrelevant thought (Buckner et al., 2008). Regions of the DM network, however, have also been found in tasks of unpredictable switching, planning future behavior, mental search, semantic and episodic memory, and signaling environmental change (Fransson, 2005; Fransson & Marrelec, 2008; Greicius et al., 2003; Mayes & Cermak, 2000; O'Connell & Basak, 2018; Pearson, Heilbronner, Barack, Hayden, & Platt, 2011). Reactive control relies upon association regions to re-activate contextually-bonded information for stimulus comparisons (Braver et al., 2007). The regions within the DM network known to be involved in episodic memory and these association regions are one and the same. This extrapolates our perception that good learners in complex tasks are

the individuals who will rely upon reactive control to perform a task with unpredictable expectancies. This would suggest that training in a task with unpredictable probe-cue expectancies (Experiment 1) would be exercising the same regions that better learners in complex tasks utilize (Experiment 2).

The unique use of individual differences in participants' ability to learn a novel task, whether a working memory task (Experiment 1) or a complex task (Experiment 2), suggests that better learners have a stronger relationship between working memory and complex tasks. In Experiment 1, we found that better learners in the unpredictable expectancies group resulted in more robust transfer to complex tasks. In Experiment 2, we found that better learners in two independent complex tasks resulted in more robust between-network connectivity during tasks with unpredictable probe-cue expectancies (Dual task and Memory Updating). These results suggest that if our goal is to engender transfer to untrained cognitive constructs, the best strategy is to employ a task that uses neural mechanisms which underlie these same untrained constructs. Training in a task biasing reactive control, such as a working memory task with unpredictable expectancies, will train the neural markers of episodic memory (MTL) and inhibition (ACC) and benefit not only those who learn quickly, but also those who are at an initial deficit in the task.

An important future direction would be to conduct the same functional connectivity analyses from Experiment 2, but to also implement a within-scanner working memory updating task with predictable probe-cue expectancies. The primary hypothesis of this dissertation is that unpredictable probe-cue expectancies are related to complex tasks. The results of Experiment 1, specifically for analyses investigating the primary hypothesis, and current methodology of Experiment 2 does not allow us to refute that predictable probe-cue expectancies are also related

to complex tasks. Using learning rates for complex tasks to predict functional connectivity during a predictable working memory updating task would provide neural correlates that differ from those found from the unpredictable working memory updating task analyses. Conversely, if the neural correlates are the same, we have evidence as to *why* both the predictable probe-cue training and the unpredictable probe-cue training resulted in significant transfer to a complex task composite score in Experiment 1.

### 4.3 Conclusions

In the two experiments presented in this dissertation (Chapters 2 and 3), we were able to investigate the relationship between working memory and complex tasks by targeting one aspect of working memory: probe-cue expectancy. We advanced our understanding of how to enhance transfer following cognitive training and discovered the neural correlates that better learners of a complex task use during a working memory paradigm with unpredictable probe-cue expectancies. The importance of understanding the details of how complex tasks relate to working memory lies within the promise of cognitive intervention. The ability to perform complex tasks is necessary for everyday living. Individuals innately have different abilities to perform such complex tasks, therefore, developing interventions that increase complex task aptitude could help equate these individual differences in ability. In the current dissertation we used two methodological approaches to propose that probe-cue expectancy during a working memory task may be the feature to target in future interventions to increase complex task performance. Although there are some limitations, the findings across the two studies converge to form a larger picture of how probe-cue expectancy in working memory tasks is related to

complex task performance and further suggests a promising route for future intervention studies:  
unpredictable probe-cue expectancies.

## APPENDIX

### ADDITIONAL ANALYSES

#### 1. Principal Component Analysis on Complex Tasks

A principal component analysis (PCA) was conducted on the 8 behavioral variables included in the complex task composite. An initial analysis found 3 components with eigenvalues over Kaiser's criterion of 1 and in combination explained 57.07% of the variance. Table A1 shows the factor loadings for these three components. We used the largest eigenvalue for each variable to identify component loading. Component 1 included CVOE global switch cost, RAPM, Trails B – Trails A, and Simon cost. This is a mix of reasoning task switching, and inhibition measures. Component 2 included Task Switch global switch cost and Associative Memory reaction time; this is a mix of episodic memory and task switching measures. Component 3 included 30-minuted delay Story Recall and Flanker Cost, this is a mix of episodic memory and inhibition measures. We conducted separate ANCOVAs on these component measures, controlling for pre-test measures, to investigate training related change.

The ANCOVA conducted on Component 1 found a significant difference for training groups,  $F(2, 63) = 4.13, p = .02, MSE = .25, \eta^2_p = .12$ . Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of training group was driven by differences between the predictable working memory training group and the control group ( $p = .02$ ), however, the predictable expectancies training group and the unpredictable expectancies training group did not differ in Component 1 scores after 10 hr of training ( $p = .69$ ), nor did unpredictable expectancies training group and the control group ( $p = .20$ ). The ANCOVA conducted on Component 2 did not find a significant difference for training groups,  $F(2, 55) = 2.06, p = .14$ ,

$MSE = .39$ ,  $\eta^2_p = .07$ . Lastly, the ANCOVA conducted on Component 3 found a significant difference for training groups,  $F(2, 64) = 5.98$ ,  $p = .004$ ,  $MSE = .45$ ,  $\eta^2_p = .16$ . Post-hoc paired comparisons using the Sidak corrections indicated that the main effect of training group was driven by differences between both the predictable working memory training group and unpredictable working memory training group from the control group ( $p < .02$ ), however, the predictable expectancies training group and the unpredictable expectancies training group did not differ in Component 3 scores after 10 hr of training ( $p = 1.00$ ).

Table A.1. Components Matrix. Largest loadings for each complex task variable are bolded. Note. RAPM = Raven’s Advanced Progressive Matrices; GSC = Global Switch Cost; fa = false alarms

	1	2	3
CVOE GSC	<b>.72</b>		
RAPM	<b>-.68</b>		
Trails B – Trails A	<b>.68</b>		
Simon Cost	<b>.46</b>		
Task Switch GSC		<b>.66</b>	
Associative Memory Reaction Time		<b>-.64</b>	.52
Flanker Cost	.47		<b>.64</b>
Delayed Recall Story Recall		.54	<b>.62</b>

## 2. Bayes Factor Analyses

Multiple JZS Bayes factor ANCOVAs were conducted on the significant constructs from our primary hypothesis results (Rouder et al., 2012). To indicate the effect of group on performance immediately post training, we rely upon the transitive relationship of Bayes factors. For example, the model which included group and the covariate of pre-test complex task composite scores ( $BF_{10} = 24140000.00$ ) can be compared to the model of pre-test complex task

scores ( $BF_{10} = 634731.02$ ) by division. After explaining the error variance attributed to pre-test complex task scores, group has an effect on immediate post scores in the complex task composite model by a factor of 38.03. This provides very strong ( $BF_{10} = 30 - 100$ ) evidence in support of our hypothesized effect of group (M. D. Lee & Wagenmakers, 2013).

The model which included group and the covariate of pre-test scores in the inhibition construct ( $BF_{10} = 1307.17$ ), divided by the model of pre-test scores in the inhibition construct ( $BF_{10} = 39.97$ ), indicates that after explaining the error variance attributed to pre-test scores in the inhibition construct, group had a factor effect of 32.71 on immediate post scores in the inhibition construct. This, again, is very strong evidence in support of our hypothesized effect of training.

The model which included group and the covariate of pre-test scores in the episodic memory construct ( $BF_{10} = 2244.80$ ), divided by the model of pre-test scores in the episodic memory construct ( $BF_{10} = 75.37$ ), indicates that after explaining the error variance attributed to pre-test scores in the episodic memory construct, group had a factor effect of 29.78 on immediate post scores in the episodic memory construct. This is strong evidence ( $BF_{10} = 10 - 30$ ) in support of our hypothesized effect of training (M. D. Lee & Wagenmakers, 2013).

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## **BIOGRAPHICAL SKETCH**

Margaret O'Connell was born in Manchester, New Hampshire on July 22, 1989. She graduated with a high school diploma from Concord High School in 2008. After a summer course at Brown University studying Abnormal Psychology, Margaret developed her passion for psychology. She attended St. Lawrence University in Canton, New York for her undergraduate degree, and graduated in the Spring of 2012 with a Bachelor of Science, Honors Psychology. While at St. Lawrence University she practiced and developed experimental design under Alan Searlman and Serge Onyper. She then continued her education at The University of Texas at Dallas under the guidance and direction of Chandramallika Basak. She received a Master of Science in Applied Cognition and Neuroscience in 2016 and continues her studies toward PhD candidacy in Psychological Sciences.

## CURRICULUM VITAE

MARGARET A. O'CONNELL

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The Center for Vital Longevity  
1600 Viceroy Drive, Suite 800  
Dallas, TX 75235 USA

Phone (office): 972-883-3767  
E-mail: mxo120930@utdallas.edu

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### EDUCATION

2012-present                    **Ph.D. Candidate/ Psychological Sciences**  
University of Texas at Dallas  
2012-2016                    **Master in Applied Cognition and Neuroscience**  
University of Texas at Dallas  
2008                            **B.Sc. (Honors)/Psychology**  
St. Lawrence University

### RESEARCH EXPERIENCE

2012-present                    **Research Assistant**  
The Center for Vital Longevity, Lifespan Neuroscience and  
Cognition Laboratory  
Dr. Chandramallika Basak  
2012-present                    **First Year Project**  
The Center for Vital Longevity, Lifespan Neuroscience and  
Cognition Laboratory  
Testing a Hierarchical Model of Working Memory: Age and long-  
term memory's influence on verbal recognition memory  
Dr. Chandramallika Basak  
2012                            **Senior Honors Research**  
St. Lawrence University, Valuing Money through Scope  
Dr. Alan Searleman and Dr. Serge Onyper  
2012                            **Research Assistant**  
St. Lawrence University, Evolutionary Memory  
Dr. Alan Searleman and Dr. Serge Onyper

### TEACHING EXPERIENCE

Summer 2015                    **Professor**  
University of Texas at Dallas, Experimental Projects  
Fall 2017 - Current            **Teaching Assistant**  
University of Texas at Dallas, Research Methods I (Graduate  
Course)  
Spring 2017                    **Teaching Assistant**

Fall 2016	University of Texas at Dallas, Statistics for Psychology <b>Teaching Assistant</b>
Fall 2015 & Spring 2016	University of Texas at Dallas, Cognitive Neuroscience <b>Teaching Assistant</b>
Fall 2014 & Spring 2015	University of Texas at Dallas, Experimental Projects <b>Teaching Assistant</b>
Spring 2014	University of Texas at Dallas, Research Methods I (Graduate Course) <b>Teaching Assistant</b>
Fall 2013	University of Texas at Dallas, Memory (Graduate Course) <b>Teaching Assistant</b>
Spring 2013	University of Texas at Dallas, Behavioral Neuroscience <b>Teaching Assistant</b>
Fall 2012	University of Texas at Dallas, Introduction to Psychology <b>Teaching Assistant</b>
Spring 2012	University of Texas at Dallas, Cognitive Development <b>Teaching Assistant</b>
Fall 2011	St. Lawrence University, Sensation and Perception <b>Teaching Assistant</b>
	St. Lawrence University, Research Methods

## **PUBLICATIONS**

**O’Connell, M. A.** & Basak, C. (2018). Effects of Task Complexity and Age-Differences on Task-Related Functional Connectivity of Attentional Networks. *Neuropsychologia*

Basak, C., Qin, S., & **O’Connell, M. A.** (under review). Differential effects of cognitive training modules on healthy aging and mild cognitive impairment: A comprehensive meta-analysis of randomized controlled trials.

**Basak, C.**, Qin, S., Nashiro, K., & **O’Connell, M.A.** (2018). Functional magnetic neuroimaging data on age-related differences in task switching accuracy and reverse brain-behavior relationships. *Data in Brief*, *19*, 997-1007.

Nashiro, K., Qin, S., **O’Connell, M. A.**, & Basak, C. (2018). Age-related differences in BOLD modulation to cognitive control costs in a multitasking paradigm: Global switch, local switch, and compatibility-switch costs. *NeuroImage*, *172*, 146–161.  
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Ray, N. R., **O’Connell, M. A.**, Nashiro, K., Smith, E. T., Qin, S., & Basak, C. (2017). Evaluating the relationship between white matter integrity, cognition, and varieties of video game learning. *Restorative Neurology and Neuroscience*.

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Qin, S., Ray, N. R., Ramakrishnan, N., Nashiro, K., **O'Connell, M. A.**, & Basak, C. (2016). Illusory conjunctions in visual short-term memory: Individual differences in corpus callosum connectivity and splitting attention between the two hemifields. *Psychophysiology, 53*(11), 1639-1650.

## CONFERENCES AND PRESENTATIONS

### Talk:

#### 2017

**O'Connell, M. A.** & Basak, C. (2017, November). *Effects of task complexity and aging on functional connectivity of attentional networks*. Society for Neuroscience, Washington D.C.

#### 2016

**O'Connell, M. A.** & Basak, C. (2016, September). *Effects of task-complexity, video game learning, and aging on task-related functional connectivity*. Center for Vital Longevity: Science Luncheon Series, University of Texas at Dallas.

**O'Connell, M. A.** & Basak, C. (2016, August). *Testing a hierarchical model of working memory: Influence of age and long-term memory on verbal memory updating*. Dallas & Austin Area Memory Meeting.

#### 2015

Basak, C., **O'Connell, M. A.**, Qin, S., Nashiro, K., Chen, X., & Druskis, M. (2015, August). *Playing for keeps: Real-time strategy game training, aging brain, and cognition*. Presentation delivered by **M. A. O'Connell** at the American Psychological Association, Toronto, Canada.

#### 2014

**O'Connell, M. A.**, & Basak, C. (2014, November). *Testing a hierarchical model of working memory: Influence of age and long-term memory on verbal memory updating*. Developmental, Cognitive, and Social/Personality Series, University of Texas at Dallas.

**O'Connell, M. A.**, & Basak, C. (2014, October). *Testing a hierarchical model of working memory: Age and long-term memory's influence on verbal recognition memory*. Presentation delivered at Armadillo Conference, Norman, OK.

## Poster Presentations:

### 2017

**O'Connell, M. A.,** Ray, N., & Basak, C. (2017, January). *Age-related differences in the relationship between structural integrity and task-related functional connectivity in a cognitive control task.* Poster presented at Dallas Aging and Cognitive Conference, Dallas, TX.

Kashiro, N., Qin, S., **O'Connell, M.,** & Basak, C. (2017, January). *Age-related differences in task load, response compatibility and selective attention during multitasking: An fMRI study.* Poster presented at Dallas Aging and Cognitive Conference, Dallas, TX.

Ray, N., Nashiro, K., **O'Connell, M. A.,** Qin, S., Smith, E., & Basak, C. (2017, March). *Real-time strategy game training effects white matter integrity in older adults.* Poster presented at Cognitive Neuroscience Conference, San Francisco, CA.

### 2016

Basak, C. & **O'Connell, M. A.** (2016, April). *To switch or not to switch: Role of cognitive control in working memory training in older adults.* Poster presented at Cognitive Aging Conference, Atlanta, GA.

Smith, E. T., **O'Connell, M. A.,** Qin, S., & Basak, C. (2016, April). *Gray matter volumes and cognitive predictors of two types of video game learning: Multiple Factor Analysis and Mediation Analyses.* Poster presented at Cognitive Aging Conference, Atlanta, GA.

Basak, C., Nashiro, K., **O'Connell, M. A.,** Chen, X., & Qin, S. (2016, April). *Effects of RTS video game training and gaming strategies on cognition and neural activity in multi-tasking ability in older adults.* Poster presented at Cognitive Aging Conference, Atlanta, GA.

Ray, N., **O'Connell, M. A.,** Nashiro, K., Smith, E., Qin, S., & Basak, C. (2016, April). *Evaluating the relationship between white matter integrity, cognition, and varieties of video game learning: Age-related differences.* Poster presented at Cognitive Neuroscience Society Conference, New York, NY

### 2015

**O'Connell, M.,** & Basak, C. (2015, October). *Task related functional connectivity within varieties of complex skill learning.* Poster presented at Society for Neuroscience Conference, Chicago, Illinois.

**O'Connell, M., & Basak, C.** (2015, January). *Testing a hierarchical model of working memory: Influence of age and long-term memory on verbal memory updating.* Poster presented at Dallas Aging and Cognition Conference, Dallas, TX.

Nashiro, K., Qin, S., Chen, X., **O'Connell, M., & Basak, C.** (2015, January). *Age-related differences in task load, response compatibility and selective attention in task switching: An fMRI study.* Poster presented at Dallas Aging and Cognition Conference, Dallas, TX.

Basak, C., Smith, E., Chen, X., Nashiro, K., **O'Connell, M., & Martin, W.** (2014, October). *Strategy vs. action games: Aging, cognitive predictors, and neural correlates of complex skill acquisition.* Poster presented at Armadillo Conference, Norman, OK.

## 2014

**O'Connell, M., Ramakrishnan, N., & Basak, C.** (2014, April). *Testing a hierarchical model of working memory: Age and long-term memory's influence on verbal recognition memory. Influence of age and long-term memory on verbal memory updating.* Poster presented at Cognitive Aging Conference, Atlanta, GA.

Basak, C. & **O'Connell, M.** (2014, April). *Predictability counts: Determining the best strategy for memory updating training in older adults.* Poster presented at Cognitive Aging Conference, Atlanta, GA.

Basak, C., Smith, E., Chen, X., Nashiro, K., **O'Connell, M., & Martin, W.** (2014, April). *Strategy vs. action video games: Aging, cognitive predictor and neural correlates of complex skill acquisition.* Poster presented at Cognitive Aging Conference, Atlanta, GA.

Qin, S., Nashiro, K., **O'Connell, M., & Basak, C.** (2014, April). *Age-related difference in neural correlates of global and local task-switching costs: An fMRI study.* Poster presented at Cognitive Aging Conference, Atlanta, GA.

## 2013

**O'Connell, M., Ramakrishnan, N., & Basak, C.** (2013, November). *Influence of long-term memory on the two tiers of working memory.* Poster presented at the Psychonomic Society, Toronto, Ontario.

Basak, C. & **O'Connell, M.** (2013, January). *The role of attentional control in working memory training in elderly: Determining the best training strategy.* Poster presented at the Dallas Aging and Cognition Conference, Dallas, TX.