The Generalizability of Dual N-Back Training in Younger Adults

Amy E. Heffernan

Submitted in partial fulfillment of the requirements

for the degree of Master of Science

at

Dalhousie University

Halifax, Nova Scotia

November 2014

Table of Contents

List of Tables

List of Figures

Abstract

Introduction: The popularity of cognitive training has increased in recent years. Accumulating evidence shows that training can sometimes improve trained and non-trained cognitive functions, and these improvements may be related to individual differences in initial capacity and performance on the training task. The current study assessed the effectiveness of a custom-designed n-back task (the N-IGMA) versus an active control task (Blockmaster) at improving various forms of working memory capacity, attention, and fluid intelligence. Three measures of working memory capacity were considered: verbal, visuospatial and observed action. Methods: Outcome measures were assessed pre- and post-training. Nineteen healthy young adults (19-30 years of age) trained at-home for 30 minutes per day, five days a week for three weeks with either the N-IGMA (n=9) or Blockmaster n=10) at-home games. Results: Pre-post changes were observed for some outcome measures and these were equal for the N-IGMA and active control group. Outcome improvements could be due to simple test/re-test benefits or alternatively the N-IGMA and Blockmaster tasks may produce equivalent training effects. Improvements in the training tasks did not correlate with the changes in the outcome measures, suggesting improvements in the outcome measures might not be attributable to transfer of learning. For verbal working memory only, participants with higher (versus lower) initial fluid intelligence demonstrated larger improvements on the outcome measures suggesting that in future research training tasks might need to be tailored to the individual participant. Pre-assessment but not change scores were related for observed action and visuospatial working memory, consistent with some overlap between content domains. Conclusion: Despite specifically targeting working memory, the N-IGMA was not better than a visuospatial control game at improving a variety of cognitive outcome measures in this small sample. Results suggest that the individual's initial cognitive capacity might need to be considered in future training studies. Caution should be used in extrapolating the results of this study to other populations of interest (e.g., older adults or individuals with cognitive deficits) since the present investigation included relatively high functioning individuals.

List of Abbreviations Used

Operations Span – OSPAN

Symmetry Span – SymSpan

Action video game – AVG

Non action video game – NAVG

Cattell’s Culture Fair Intelligence test - CFIT

Working memory capacity – WMC

Short-term memory – STM

Long-term memory – LTM

Visuospatial sketch pad – VSSP

Phonological loop – PL

Raven’s Advanced Progressive Matrices - RAPM

Fluid intelligence - G*f*

Acknowledgements

I would like to thank my committee members Dr. D. Westwood, Dr. G. Eskes, Dr. L. Dithurbide, and Dr. M. Stone, for their support through this process. I would like to especially thank my supervisors Dr. D. Westwood and Dr. G. Eskes for their advice and assistance through the project. I would also like to acknowledge the support from Dr. R. Klein towards to completion of this project. As well, I greatly appreciate the time volunteered from: Dr. J. Salmon, Jake Kroeker, Dr. S. Jones, Kerry Clifton, Franziska Kintzel, Richard Patrick, Amanda Glenn, Janet Green and Graham Wilson, these individuals assisted with the coordination of the study and data collection. Sources of funding include the School of Health and Human Performance, Atlantic Canada Opportunities Agency (AIF fund) and NSERC Collaborative Health Research Projects (CHRP) from Dr. R. Klein and Dr. G. Eskes. And finally, I am thankful to all the participants who volunteered their time to participate in this project

Chapter 1: Introduction

Cognitive functions reflect our ability to learn, solve problems, and direct our attention to important information. Declines in cognitive function are common in older adults and individuals with acquired brain damage or disease such as stroke and Parkinson's disease (Anguera et al., 2013; Westerberg, 2007). Cognitive declines are associated with a reduced capacity to care for oneself independently, reduced rehabilitation efficacy, and reduced capacity to carry out activities of daily life (Westerberg, 2007; Klingberg, 2010). Growing evidence suggests that computer games can be used to train cognitive functions and lead to improved working memory, attentional processes, processing speed and multi-tasking abilities in older adults as well as in stroke patients (Anguera et al., 2013; Nouchi, et al., 2012; Westerberg, 2007).

Specific cognitive functions such as short-term and long-term memory can be trained using strategies that individuals can utilize when they are required to remember information; these may include mnemonics, mental imagery, and rehearsal. Such strategies are commonly taught to school children, individuals with learning disabilities, and older adults experiencing declining memory capacities and have been shown to improve working memory and long-term memory (Dehn, 2008; Bailey, Dunlosky & Hertzog, 2014). However these strategies do not lead to improvements in other tasks that are not explicitly practiced or trained (Dehn, 2008; Bailey, Dunlosky & Hertzog, 2014); in other words, there is little evidence of transfer of learning. Transfer of learning refers to the benefits realized in an untrained task as a function of another trained task. Within the field of cognitive training there is considerable controversy as to whether or not significant transfer of learning effects are possible.

A seminal study by Green and Bavelier (2003) had a significant impact on cognitive training and the development of computer and video cognitive training games. These authors reported that individuals who frequently play action video games (AVGs) with extensive graphics and fast-paced interaction (e.g., Grand Theft Auto, Halo, Call of Duty) show superior performance in many aspects of visual attention on other, untrained tasks of attention, suggesting the presence of transfer of learning effects. AVG players demonstrated increased attentional capacity, enhanced spatial attention to untrained locations, and greater task-switching abilities compared to non-AVG players.

To establish a causal connection between AVG playing time and attention capacity, Green and Bavelier (2003) took a group of non-action video game (NAVG) players and had them play either a first-person shooter AVG (Medal of Honour) or Tetris for 1 hour a day for 10 days. Tetris was used as a point of comparison because it requires interaction with a computer game, and thus activates visuomotor coordination as well as engaging visual attention. However, it differs from AVGs in the extent to which a variety of visual attention skills are engaged, and it does not involve a complex, dynamically updated environment that taxes spatial processing. Green and Bavelier found that the NAVG players who played Medal of Honour (in comparison to those who played Tetris) demonstrated improved performance on untrained visual attention tasks, and in locations within their spatial distribution not explicitly trained. The improvements seen in the NAVG players here established two important points: the first was that training-induced transfer of learning effects can occur, and the second was that although action video games might seem frivolous, playing these games results in transfer of learning effects to many components of visual attention that might prove useful in other contexts.

The transfer of learning effects seen by Green & Bavelier are speculated to occur because AVGs require players to simultaneously load multiple aspects of visual attention in order to complete several concurrent tasks such as scanning for enemies and allies, avoiding injury, and searching for health and ammunition markers (Green and Bavelier, 2003). AVGs also have high graphic-rich virtual environments, which require more attentional skills to filter relevant and irrelevant features, which are not seen in games such as Tetris. Taking from these AVG findings, the optimal goal in developing cognitive training tools is to develop programs which load multiple cognitive processes to effectively facilitate transfer of learning effects.

Currently there is a large range of cognitive training games available to the public. Many of these games market 'brain training' as a way to exercise your brain, improve processing speed, memory, and attention. A few examples of brain training games available to the public (determined by a simple Google search for "brain training") include Lumosity (http://www.lumosity.com), Fit Brains by Rosetta Stone (http://www.fitbrains.com/) and Dynamic Brain (http://www.dynamicbrain.ca/). However, even with the prevalence of cognitive training games, questions remain about their capacity to improve general cognitive functions and ultimately lead to transfer of learning effects in untrained tasks.

In a noteworthy study by Owen et al., (2010) 11,430 adults between the ages of 18-60 completed an online cognitive training study. The study included pre- and post-training outcome measurements of reasoning, verbal and spatial working memory and paired-associates learning, tasks that were not explicitly part of the training game. There were 2 experimental groups. The first group played games that focused on reasoning, planning, and problem-solving abilities. The second group played games that targeted short-term memory, attention, visuospatial processing and mathematics, A third group was a control group that simply answered questions but did not take part in any training. Participants were asked to practice for a minimum of 10 minutes a day 3 times per week for a 6 week period.

Owens et al. found that all 3 groups improved performance on the given tasks but no gains were seen in the untrained tasks. While the two experimental groups improved on the pre- to post- outcome measurements, these improvements were no better than those seen in the control group, which suggested that improvements might simply be due to the repetition of the outcome measures rather than legitimate transfer of learning effects. This study had several flaws. All age ranges were analyzed together, potentially inflating error variance due to the cognitive declines associated with increasing age, and furthermore participants were included so long as they completed a minimum of two training sessions over the course of the 6 weeks, which is only an 11% completion rate. Nevertheless, this monumental study calls into question the assertion that cognitive training is effective and that training can transfer to other tasks.

A recent study by Clouter (2013) investigated a cognitive training tool known as Brain Workshop (http://brainworkshop.sourceforge.net/), which is specifically designed to target working memory. The Brain Workshop utilizes an n-back working memory task, which requires participants to continually update information they are holding in mind and discard information that is no longer relevant. The task requires participants to monitor a stream of information and to detect items that match at varying levels of separation (the '*n*-back' level). Participants generally start at an N=1 level (i.e., detecting matches for items that occur immediately after each other) and adaptively progress to more difficult levels as their mastery of the task increases.

Clouter (2013) had 2 groups; one was an experimental group who progressed adaptively through Brain Workshop whereas the active control group stayed at a 1-back level for the duration of the study. Transfer of learning effects were determined by comparing pre- and post-training measurements of fluid intelligence (measured by Cattell's Culture Fair Intelligence [CFIT] test which contains 4 subtests), reasoning, attention (measured by the Stroop task), and visuospatial and verbal working memory (measured by the symmetry span and operation span task, respectively). Participants in both groups were required to complete 15, 30 minute training sessions over the course of 3 weeks.

Over the course of the 3 week training intervention both groups demonstrated task-specific performance increases; the experimental group improved N-levels while the control group improved response times. Clouter's (2013) primary question addressed whether the experimental group would show greater gains than the control group on the (untrained) outcome measures. It was found that both groups improved on the measures of fluid intelligence with the experimental group significantly outperforming the control group. Both groups improved visuospatial and verbal working memory. There were small but significant improvements in attention however these were similar for the two groups.

To further investigate the gains in the outcome tasks for the two groups Clouter (2013) used the median score of the pre-training CFIT score to subdivide each group into high and low scorers. This split permitted an assessment of the potential modulating effect of initial fluid intelligence level. The results indicated an association between initial CFIT score and improvement in CFIT scores (higher initial scores predicted higher change) in the experimental group but not the active control group. Furthermore, in the experimental group individuals with higher initial CFIT scores decreased their response times in the Stroop task. These findings highlighted that initial intelligence may be an important variable to consider when investigating transfer of learning effects due to cognitive training. It is possible that certain variables such as fluid intelligence may predict the success or provide insight to limitations of cognitive training efficacy.

Clouter (2013) attempted to discern whether individual performance on the training task predicted gains in the outcome measures, as would be expected if transfer of learning effects were occurring. Somewhat surprisingly, Clouter found that improvements over the training sessions, measured by the slope of average daily N-level achieved, did not predict improvements in the outcome measures. However, the individual difference in initial starting N-level (measured as the N-level intercept) was related to changes in the outcome tasks. Specifically, individuals who started at lower N-levels demonstrated gains in fluid intelligence, verbal working memory, and fewer errors in the Stroop task. Individuals with higher starting N-level demonstrated reduced response times during the Stroop task, suggesting a change in attentional capabilities. Thus, it appears that the connection between training and transfer of learning effects is not straightforward, and might be dependent upon the individual's initial cognitive capacity.

In a study using a 3-week long n-back training task with children (mean = 9 years of age), Jaeggi et al., (2011) found that gains in the trained task were positively associated with gains in fluid intelligence. The fluid intelligence scores of the children who showed low training gains were no different than a control group who trained on a knowledge and vocabulary task. In contrast to Clouter (2013), Jaeggi et al.'s findings suggest a clear linkage between training performance and transfer of learning. Given this discrepancy, there is a clear need for further research that considers the interaction between individual differences in initial cognitive capacity and performance on the training task and transfer of learning effects.

The widely discrepant findings in the cognitive training and transfer literature suggest that there are many variables that influence the efficacy of cognitive training tools and the potential to see transfer of learning effects. Some of the complexity might be due to the uncertain degree of overlap between "distinct" cognitive functions such as working memory, attention, and fluid intelligence (Jaeggi et al., 2011) and because training tasks may overlap with outcome measures in some studies but not others (Jaeggi et al., 2008). For example, working memory is proposed to consist of relatively distinct verbal and visuospatial subsystems, but the OSPAN and the symmetry span task (SymSpan task), which allegedly measure the two different systems, share 70 -85% of their variance (Kane & Engle 2003). The OSPAN requires participants to remember a list of words while performing distracting mathematical equations, and the SymSpan requires participants to remember the position of a red square in a 4 x 4 matrix, while performing distracting judgments of visual symmetry.

When exploring transfer of learning effects, it is likely important to consider the relative similarity of the training and transfer tasks (Nouchi et al. 2012; Karbach and Kray, 2009). Far transfer refers to outcome tasks that are not closely related to the trained task (Nouchi et al. 2012; Karbach and Kray, 2009). For example, fluid intelligence likely depends upon working memory but also many other cognitive functions, so it is not obvious that n-back training, which emphasizes only working memory capacity, should transfer to fluid intelligence; this is an example of far transfer. Near transfer refers to outcome tasks that share many features with the trained task, such as evaluating the effects of n-back training on a different form of working memory capacity.

Most studies of working memory and transfer of learning effects emphasize verbal and visuospatial modalities, consistent with the dominant model of working memory (Baddeley, 2007). There is no research, to the author's knowledge, which explores the transfer of learning between verbal or visuospatial working memory training and working memory for observed action. Working memory theorists disagree about whether memory for action is merely a component of visuospatial working memory (e.g., Baddeley, 2007) or perhaps a distinct, third working memory slave system (e.g., Wood, 2007). Memory for observed action plays a crucial cognitive role in our ability to attend to, process, and remember, observed actions, functions imperative to our ability to learn movements, influence social interaction and help understand the behaviours of those around us.

Drawing on the concept of near versus far transfer, one might expect to find an association between gains in different working memory capacities if systems overlap. In other words, one might predict that gains in visuospatial working memory might be more closely related to gains in working memory for observed action compared to verbal working memory. Alternatively, if all three systems are distinct, there might be no correlation between the gains found in each capacity. The substantial role of working memory for observed actions in our ability to interact with the world, and the current void of research investigating whether it is susceptible to the transfer of learning effects, warrants a further exploration.

The current study has three goals. The first goal is to further explore the question of whether working memory training produces transfer of learning effects for fluid intelligence and attention. The second goal is to determine if a custom-designed working memory training game, known as the N-IGMA, produces greater transfer of learning compared than an active control game (Blockmaster, a modified version of Tetris). Finally, the third goal is to explore the properties of working memory for observed action in relation to other working memory domains, cognitive training, and transfer of learning effects.

The experimental group in the study trained with a custom-designed n-back working memory game called the N-IGMA. The N-IGMA includes verbal and visuospatial working memory components and requires participants to update, store, and discard information on a continual basis. Furthermore, it is designed to be engaging to the participants with pleasing graphics, feedback, and adaptive characteristics intended to maintain an optimal level of difficulty. The active control group played a visuospatial interactive game called Blockmaster, a customized non-adaptive version of the popular block arranging game Tetris. Blockmaster does not appear to require significant working memory capacity, as it only requires focus on one object at a time. Nevertheless, Blockmaster does require visuospatial processing, attention, and interaction with a computer and therefore provides a control for the possible benefits of each of these factors on various cognitive outcome measures.

Participants completed a 3 week, 15 session intervention, modeled on a similar training protocol used by Clouter (2013). Twenty-four healthy young participants between the ages of 19 – 30 were recruited for the study. This age group was chosen to minimize any systematic decline of cognitive functions that has been shown to occur in healthy populations after the age of 20 (Park & Reuter-Lorenz, 2009). Although the N-IGMA is intended as a tool to address cognitive decline in aging and after neurological injury, this initial exploratory study focused on a restricted range of age and cognitive status to minimize error variance and thereby maximize statistical power to detect training and transfer effects.

Outcome measures included fluid intelligence, attention, visuospatial and verbal working memory capacity, and observed action working memory capacity and these were collected before and after the training intervention. The change in the transfer tasks from pre- and post-training was compared between the experimental and active control groups. To minimize tester bias, those administering the assessments were blinded to the participant group assignment.

It was hypothesized that (1) compared to the active control group, the experimental group (N-IGMA group) would exhibit significantly higher improvements for all outcome measures including fluid intelligence measured by the CFIT, attentional control measured by the Stroop task, and working memory span measured by the Operation Span, SymSpan, and MoveSpan task; (2) gains in the outcome measures would be positively correlated with gains in the N-IGMA training game over the intervention period; (3) gains in the outcome measures would be greater for individuals with higher CFIT scores prior to beginning the intervention; (4) correlations between MoveSpan and

SymSpan tasks will be higher than correlations between the MoveSpan and OSPAN tasks.

Chapter 2: Literature Review

A recent surge in marketing from international companies such as Lumosity (www.lumosity.com) has brought brain training to the forefront of attention within the general public. The selling feature of many brain training games is the importance of cognitive function and how improving 'brain power or capacity' will help individuals improve their memory, attention, and reasoning in day-to-day life.

The concept of brain training has more to it than clever advertising and cellphone apps. Improving cognitive function, through the development of interactive computer tools/games, is a field of interest that may benefit populations that demonstrate lower or declining cognitive function such as children with learning disabilities, patients with an acquired brain injury (e.g. Stroke patients), and older adults.

Cognitive function is a broad term that encompasses functions such as working memory, control of attention, and fluid intelligence (Owen, et al., 2010; Baddeley 2000; Baddeley 2003). Working memory, which is the focal point of this review, is the ability to hold information for a brief period of time and the ability to manipulate this information. Working memory has significant and broad implications for our daily lives ranging from providing the link between perception, action and long-term memory, too influencing our ability to learn and think (Dehn, 2008; Baddeley 2003). Moreover, working memory capacity is a reliable predictor of academic achievement, career success, mathematic skills, problem solving, reading skills and a general indicator of an individual's ability to care for themselves independently (Dehn, 2008; Jarrold & Towse, 2006; Klingberg, 2010). In this review, I will focus on the systems and the neural substrates of working memory. I will also review interventions for training working memory and their implications for transfer of learning to other non-trained cognitive functions.

Short-term, Long-term and Working Memory

The human capacity for memory influences nearly every daily activity. The general term memory can be considered the ability of organisms to benefit from a previous experience that induces change (Magill, 2010). Throughout the last century, our understanding of memory has slowly been evolving. In 1949, Donald Hebb proposed a two-component system of memory with short term and long-term memory (Hebb, 1949). In this model, the short-term system was a temporary storage system, having temporary neural changes, while the long-term system resulted in permanent neural changes and storage of information (Baddeley, 2007). Though these components are still relevant to our current understanding of memory today, updated models now include an active working memory system in contrast to the more static short-term memory system proposed by Hebb. In newer models, working memory is considered a fluid system that is always changing, and information in this system decays quickly without being rehearsed.

While working memory includes the concept of information storage (e.g. short term memory), it differs from short term memory as it further adds the notion of information manipulation and attentional control (Baddeley, 2007; Baddeley, 2003; Dehn, 2008; Jarrold & Towse, 2006). The term short term memory (STM) is still used to describe simple tasks that temporarily store a limited amount of information used for immediate recall (Kane, Conway, Mirua, Colflesh, 2007).The term long-term memory (LTM) is also still used, and is understood as a crystalized system in which neural changes are permanent, leading to long-term shortage of knowledge (exploring LTM and crystalized systems are beyond the scope of this review; Baddeley 2007).

A Working Memory Model

The present review emphasizes the four-component model proposed by Baddeley (2003) as a refinement to the broadly accepted three-component model of Baddeley and Hitch (1974). The four components of this system include the phonological loop, the visuospatial sketch pad (VSSP), the episodic buffer, and the central executive. The principal feature of this complex system is that each component has a limited capacity of information it can hold at one time (Zimmer, Munzer, & Umla-Runge, 2010). Below I will discuss each of the four components in the working memory model, and discuss a current limitation of the whole model as it does not include any specific consideration of working memory for observed actions.

The phonological loop. The phonological loop, the better understood component of the model, is thought to have evolved to support language acquisition in humans (Aboitiz, Aboitiz & Garcia, 2010), and it contains two subsystems. The first subsystem is responsible for short-term storage of auditory information, such as words and sounds, and it decays quickly without conscious rehearsal of the item to be remembered. The second subsystem is used for subvocal speech (thought of as our internal speech), and articulatory rehearsal. There are several findings that support the existence of the phonological loop. These include: limited capacity of verbal short term memory (Baddeley, 2003; Repovs & Baddeley, 2006); the phonological similarity effect in which dissimilar sounding letters are easy to remember and recall (Larsen, Baddeley, Andrade, 2000; Baddeley, 2003); irrelevant sound effect in which irrelevant speech presented during or between a to-be-remembered list (words, sounds, letters) affect serial recall (Larsen et al., 2000); and lastly articulatory suppression, that when used in a dual auditory task prevents participants from using articulatory rehearsal impairing the phonological loop's ability to hold information (Baddeley 2003; Repovs & Baddeley, 2006). In summary, the phonological loop is considered a domain-specific slave system responsible for auditory working memory and articulatory rehearsal. In the working memory model, the concept of a slave system is that the subcomponents of working memory exist to help serve the central executive.

The visuospatial sketch pad. The VSSP is also a domain-specific slave system used to hold and code visual and spatial information; however it is not as well understood as the phonological loop. This VSSP is thought to have evolved to assist with visual recognition of tools and objects, and for forming spatial representations used for orientation in our environments (Baddeley, 2003). Similar to the phonological loop the VSSP is separated into two distinct subsystems: the first being a visual system and the second being a spatial system. These subsystems can be considered the 'what' and 'where' working memory systems (Passolungi & Mammarella, 2012; Baddeley, 2003). The visual system is responsible for holding shapes and colors or objects, while the spatial system holds spatial information such as location. Interestingly, limitations of the spatial system have been shown to predict decreased mathematics performance in children with mathematic learning disabilities, although there are generally corresponding limitations of attentional control as well (Passolungi & Mammarella, 2012).

The central executive and episodic buffer. The central executive, unlike the phonological loop and the VSSP, is a domain-general system (Zimmer et al., 2010). The central executive is often also considered the supervisory attentional system, and is responsible for dividing, switching, and focusing attention, as well as linking working memory to long-term memory. The central executive is believed to integrate and manipulate information stored with in the phonological loop and VSSP. The central executive is one of the most important systems of working memory, as without the ability to filter and select information we would not be able to interact with our environments with such ease.

The central executive, unlike the phonological loop and the VSSP, does not hold information and as such does not have its own storage location. Instead, it is now believed it uses the episodic buffer as a workspace. Here in the episodic buffer, information held by the phonological loop and the VSSP can be integrated and is thought to be where information becomes available to conscious awareness (Baddeley, 2007). Thus providing some solutions to limitations of the older three component model which did not explain how different codes from the VSSP, the phonological loop and LTM were integrated. The episodic buffer is the newest addition to current working memory model proposed by Baddeley (2003) and it is still not fully understood.

Limitation of the current working memory model. As demonstrated above, the working memory model thoroughly describes how we code and store visual, spatial and verbal information, however there is little agreement on how we code and where we store information regarding observed actions (Wood, 2007). Our ability to hold and store information regarding observed actions is important for learning actions and performing motor tasks (Baddeley, 2007). It is thought that as we observe action we break the movement into discrete units of action and then piece the action together after observation, therefore we need a place to store these discrete units and piece them together (Zacks & Tversky, 2001).

Within the current working memory model it is speculated that the VSSP is responsible for observed action. Available research however provides controversial evidence regarding where observed actions are held and coded. Baddeley himself acknowledges there is more research needed to explore working memory for observed action (Baddeley, 2007). Within the last 30 years evidence has suggested that observed actions may have its own system (Smyth & Pendleton, 1989), that it may be an aspect of the VSSP, or that some components of observed action may be verbal coded (Wood, 2007); to date there has been no general agreement or consistent inclinations on which system is responsible. It is thought that such variability in evidence deciphering whether there is a kinaesthetic subsystem is due to the complex tasks needed to separate from visual, spatial and verbal working memory systems (Baddeley, 2007).

Working memory capacity

Working memory is a limited capacity system, which can also be thought of as a limited 'span' as we are unable to attend to and remember all of the incoming information. Thus, we are only able to remember a certain span of important or relevant information. Capacity, therefore, represents the span of stimuli we are able to attend and remember at once (Baddeley, 2007). Originally Miller in 1956 determined that humans have the short term memory capacity for 7 +/- 2 pieces of information (Baddeley, 2007;

Cowan, 2010; Miller, 1956). Recently however, working memory capacity (WMC) has been considered more on an individual level, as it varies greatly from person to person (Cowan, 2010). It is this individual variation of working memory capacity that is most important to consider when investigating working memory and its relationship to other cognitive functions.

WMC is often measured using simple span and complex span tasks. In a simple span task, participants are required to remember and immediately recall a list of digits, objects, or locations. Most believe that simple span tasks, such as a digit span task, measures short-term memory. Simple span tasks do not involve any distractor task, used to interfere or prevent the rehearsal of the information. Such distractor tasks are used for complex span tasks which require participants to retain a list of to-be-remembered information while completing additional tasks or distractor tasks. An example of a complex span task is the Operation Span (OSPAN) that requires participants to hold a list of to-be-remembered words while preforming mathematical operations (Dehn, 2008).

A different style of a complex span task is the n-back task which requires participants to continually update a list of running auditory and/or visual stimuli with the goal of detecting and identifying matching stimuli over a span of '*n*' items (Jarrold & Towse, 2006). The n-back is considered a working memory task, as participants are required to continually discard information that is no longer required and update relevant new information simultaneously. This type of task focuses on active working memory process for retention and manipulation. The use of these and other types working memory span tasks provide information and can be used to assess individual differences of WM and associated capacity (Jarrold & Towse, 2006).

Individual differences of WMC are highly predictive of other cognitive functions such as fluid intelligence, reasoning, attentional capacity, as previously detailed. For example, Conway and colleagues (2002) tested 120 young healthy adults on several measures of WMC (including the Operations span task; OSPAN, Reading span task, and Counting span task) and fluid intelligence (Raven's Progressive Matrices, RAVENS and Cattell's Culture Fair Test; CATTELL), and found positive correlations between the WMC test and the fluid intelligence test scores. They ventured from their results that the control of attention (governed by the central executive) could be an underlying neural link between working memory and fluid intelligence. The speculation that attentional control underlies WMC and fluid intelligence is a commonly shared theory (Unsworth and Engle, 2005). Findings linking these paradigms are often flawed by poor study design. This is demonstrated by Unsworth and Engle (2005), who were unable to link WMC and fluid intelligence; however they only used one WMC measure and one fluid intelligence test but none the less they still believe attention is the underlying neural link. While the evidence is still mounting there is reason to believe that working memory, fluid intelligence, and attentional control are all closely linked and this link by occur on a neural level as they may all share a common neural network.

Cognitive Training

Training tools to improve working memory have been an interest of research for many years and have recently surged in the marketing of complex interactive computer tools. The current surge of interactive computer tools or games used to try and target working memory and facilitate transfer of learning. Transfer of learning occurs when improvements are seen in the trained cognitive function as well as other untrained cognitive functions (Jaeggi et al., 2010). The quest for the most effective cognitive training tool or 'brain exercise' with the ultimate range of transfer of learning is driven by the need for an effective intervention that has the greatest amount of benefits, and that can be applied to a range of target populations (Green & Bavelier, 2008). Similar quests for the best exercise with the broadest range of benefits can be seen in physical health research. For example, researchers are always searching for the best exercise with the largest range of health benefits to try and promote physical health and reduce disease.

There are several training tools used to train working memory as well as other cognitive processes. For example the Cogmed Working Memory Training (Cognitive Medical Systems) is a training tool which includes four tasks; a visuospatial WM task, a backwards digit span task, a letter span task, and a choice reaction time task (Klingberg, Forssberg &Westerberg, 2002) . The first three tasks target WM while the latter targets attention. The visuospatial WM task and the letter span task are forward span task requiring participants to recall items from the first to the last. Alternatively, the backward digit span task is backward span task requiring participants to recall items from the last to the first item given. This type of forward and backwards span task differ from other types of working memory training such as the n-back task, described in detail below, which targets working memory processes such as a recognition, updating, and inhibition (Kane et al., 2007). These different forms of training have led to various positive effects of transfer of learning to different cognitive function (Klingberg, 2010). Transfer of learning effects from various forms of training tools are detailed below (in the section title: cognitive training and evidence for transfer of learning).

The n-back task. The n-back task is another tool used to improve working memory which requires holding and manipulating information simultaneously. The n-back task initially was used in the 1990's as a tool for examining immediate working memory during fMRI studies (Kane et al., 2007). Since then the n-back task has moved to the forefront of working memory research as an assessment and training tool. The n-back task engages several processes simultaneously by requiring inhibition of irrelevant cues, updating visual and/or auditory representations, maintenance, and target selection (Jaeggi, Buschkuehl, Jonides, Perrig, 2008).

The n-back task can include auditory stimuli (e.g. words or letters) and/or visual spatial stimuli (e.g. spatial locations of squares in a matrix), which are to-be remembered. Thus the n-back task can be in a single visual or single auditory task, or a dual task presenting visual and auditory cues simultaneously. The task requires participants to indicate matches of the stimuli that occur on '*n*' trials. For example, if a participant was on N=1 level (an 1-back) they would be required to indicate matches that occur back-to-back (1-back); therefore if the participant was given an auditory string of 2, 3, 5, 5, 6, 3, they would acknowledge a match with a key press when they heard the 4^{th} auditory stimulus, which is a 5, as it is a back-to-back match (1-back) to the 3^{rd} auditory stimulus, as it is also a 5. Likewise, if the participant was on N=3 level (3-back) they are required to indicate when a current stimulus matches to that which occur three stimuli before; for example if the participant was given an auditory string of 2, 3, 5, 6, 3, they would indicate a match on the 5^{th} auditory stimulus, which is a 3, as it is a match to the stimulus given 3-back which was also a 3. Participants generally start at an N=1 level and adaptively progress to more difficult levels as their mastery of the task increases.

The sensitivity of load, or difficulty, as participants progress through N-levels is often seen starting at N=3, and is generally measured by a decline in accuracy of responses (Jaeggi et al., 2010). There are two interesting findings that can be seen with load sensitivity in the n-back task. The first finding is that visuospatial stimuli are easier to recall than auditory stimuli for some individuals, and thus less sensitive to load. (Jaeggi et al., 2010; Jaeggi, Schmid, Buschkuehl, & Perrig, 2009). Secondly, sensitivity to load changes with age: young adults often out-perform older adults as load increases (Jaeggi et al., 2009). These findings demonstrate the importance of difficulty, and the differences between the capacities of the different working memory systems involved during the n-back task.

Principles of Learning: What we can learn from Action Video Games

As previously detailed, our current knowledge regarding the principles of learning which facilitate transfer of learning comes from the study of action videos games (AVG) and their beneficial effects on cognitive functions. AVG players play games for reasons such as: they find them engaging, they are motivated to succeed and attain better scores, and the graphics are appealing. In order to succeed AVG players must use short-term and long-term memory to recall virtual maps of the game layout including different terrains, task goals per level, and virtual locations of things such as health boosters or save zones. As well, AVG players are given feedback via scores and rewards, and the difficulty of the game is generally progressive, preventing players from becoming discouraged and giving up. These attributes of AVGs target different aspects of principles of learning and different cognitive function. This leads to AVG players to demonstrate better attentional capacity, improved visual attention control, and spatial distribution of visual attention, as well as enhanced task-switching abilities, when compared to aged-matched non-video game players (Green & Bavelier, 2003). Principles of learning such as repetition, task difficulty, motivation, and feedback, encompassed by AVG should be considered when constructing cognitive training tools to which transfer of learning is a primary outcome goal.

Task difficulty. While playing AVG, progression of difficulty is based on how well an individual performs at a lower level. The manipulation of task difficulty allows participants the ability to learn new skills and techniques that will help them as they progress to more difficult levels (Green & Bavelier, 2008). As discussed previously, load during the n-back task has important implications on the success of identifying correct matches. Often seen in the construction of the n-back task, participants begin at n=1, and as they are able to master levels, progress to more difficult levels, similar to AVG. Also, some n-back tasks are built so that if a participant is unable to succeed at a higher level, they regress to the previous level. This helps the participant improve their skills, ensuring the difficulty does not hinder success or motivation of the task (Jaeggi et al., 2008).

The adaptation of task difficulty is also sometimes done prior to the start of a task. Anguera et al., (2013) determined the best starting difficulty level for their cognitive multitasking computer game prior to the onset of training, and used adaptive algorithms for progression and regression during training. This was to ensure that participants played the game at an optimal challenge level. This also ensured that differences in outcomes measures did not reflect differences in skills and abilities, as well as ensuring maximal engagement in the task.

Often if a task is perceived as too difficult participants, will disengage from the task and negatively influence outcome measures. The negative influence of task difficulty on learning outcomes was seen by Jaeggi et al., (2011). They discovered that while training children (approximate average age of 9) on an adaptive dual n-back task, the children that reported the task was difficult and effortful were significantly less likely to demonstrate improvement.   In summary, there is an optimal threshold of difficulty that leads to maximal engagement, motivation, and learning.

Motivation and wakefulness. Action video games are thought to target motivation and arousal because of their high graphic content and programming. Programming often engages the player by pretending they are a character in a story or in a mission. Additionally, motivation and arousal are captured by alertness and wakefulness. This is often done as a result of intensity. Intensity of a game often leads to increases of heart rate, breathing rate and can induce some level of anxiety. These increases in arousal help engage and maintain motivation and ultimately help improve learning outcomes (Green & Bavelier, 2008).

While taking into consideration the importance of motivation and arousal, Jaeggi et al., (2011) constructed a custom dual n-back task for children using high graphic content and themes that were assumed engaging for children. For example, they used a lily pond with frogs for visual/spatial location cues, and constructed a story that accompanied each theme. These themes changed every five training sessions to ensure maximum arousal and engagement from the children. Self-reports from the children involved determined they did enjoy the game and found it fun. This highlights that motivation based on themes and graphics needs to be tailored to the target audience.

Feedback. While motivation provided from game presentation is important, a factor that engages motivation as well as promotes learning is feedback. The principle of feedback is important in all domains of learning, from perceptual, to motor, and to cognitive (Green & Bavelier, 2008; Klingberg, 2010). Performance feedback, when an individual has met a certain criteria, often occurs in the form of rewards. This reward feedback is common in AVGs (e.g., when a mission is complete, a player receives rewards in the form of coins or more tools they can use to succeed in higher levels).

Again, Jaeggi et al. (2011) provides an example of implementing rewards for motivation. In their custom dual n-back task for children, they used a point collection system, such that when the children successfully completed a block of N-levels, they received a set amount of points. The children were able to use these points as cash to purchase stickers or pencils. Alternatively, Anguera et al., (2013) provided positive feedback in the form of fun facts. Therefore, when a participant completed a certain number of trials, they were rewarded with a fun fact about basic human physiology. This highlights the novel ways in which feedback can be integrated to maintain motivation and help facilitate learning.

Cognitive Training and Evidence for Transfer of Learning

General working memory training interventions are easy to find online. These include, but are not limited to, Lumosity (http://www.lumosity.com) and PositScience (http://www.brainhq.com). These online training tools and the popularity of some of them highlight how accessible training tools need to be. The creation of a general interactive cognitive training tool that is beneficial for any population comes at a cost and it is often seen as a reduction in the effectiveness of the training tool. This is demonstrated by Owen et al., (2010) who implemented a 6-week online cognitive training study. The study recruited 11,430 participants who were randomly assigned to either, a) a training group for reasoning, planning and problem-solving, b) a second training group for short-term memory, attention, visuospatial processing and mathematics, or c) a control group who answered random knowledge questions. Their goal was to assess transfer of learning to outcome measures, which included reasoning, verbal short-term memory, spatial working memory, and paired-associates learning. The outcome measures were taken at baseline prior to training, and at 6 weeks post training. Owens and his colleagues (2010) found no transfer of learning between any group, and found similar improvements between their training groups and their control groups. This study highlights the many flaws of widely available cognitive training tools. One major flaw was no division of age groups in either training outcomes or outcome measures. It is known that as we age, past our twenties, cognitive abilities including reasoning and working memory start to decline in normal populations (Park & Reuters-Lorenz, 2009). It appears in their analysis Owens et al. (2010) did not account for the linear decline of cognitive function that occurs with age, which may have resulted in significant variance within their data.

Also, as previously discussed, training tools should be tailored to specific target populations. For example, within the Owen et al. (2010) study, younger adults may have found the activities more or less motivating than an older adult who would be expected to influence attrition, and would ultimately influence outcomes (Anguera et al, 2013; Green & Bavelier, 2008). Lastly, the participants in Owen et al.'s (2010) study only engaged in the training tasks for a minimum of ten minutes for 3 days a week, thus they may not have been engaged for long enough to elicit neural plasticity required for transfer of learning. While Owen and colleagues (2010) study had good intentions, the design was not strong enough to generalize the findings that cognitive training does not lead to transfer of learning.

While it is important to see transfer of learning in older adults, individuals with acquired brain injury are also key target populations for working memory training. A pilot study by Westerberg et al, (2007) investigated the use of an online at-home cognitive training software program (RoboMemo © from Cogmed Cognitive Medical Systems AB, Stockholm, Sweden) on stroke patients 1 – 3 years post injury. Their study provides insight to the benefits of properly constructed and managed online cognitive training program and how beneficial they can be, unlike the aforementioned Owens et al., (2010) study. The program used by Westerberg et al., was originally designed for children with ADHD, and included several adaptive visuospatial and auditory working memory tasks that required participants to hold and update information. The training required 40 minutes a day, 5 days/week, for 5 weeks.

Participants recruited by Westerberg et al. (2007) were required to complete a battery of neuropsychological tests pre and post training to assess attentional capacity, reasoning, intelligence, and WMC. As well, participants completed a survey for cognitive failures in daily life that target attentional and memory difficulties. Results demonstrated that participants improved significantly on non-trained attentional control and working memory tasks. Also, there were significant improvements in daily reported cognitive failures. Other studies which have used the computerized Cogmed WM training tool have similarly reported improvements in word span, complex WM span, attention (measured by the Stroop task and go/no go), and mathematical reasoning (Klingberg, 2010).

A significant limitation to the pilot study by Westerberg et al. (2007) was the lack of an active control group. An active control group should engage participants in an activity that would require the same time and daily engagement as the training group, but does not require working memory processes. Active control groups mirror the idea of placebo groups in drug trials, and can be used to measure other aspects such as computer use and compliance (Klingberg, 2010). Lack of active control groups is a wide limitation of many cognitive and working memory training studies, as many use no-contact control groups instead (Klingberg, 2010). Regardless, the results from Westerberg et al. (2007) provide promising implications for improving cognitive function and for the transfer of learning in individuals who have suffered an acquired brain injury, such as a stroke. The results from Westerberg et al. (2007) provide evidence that attentional control and working memory processes can be improved with interactive, engaging, and adaptive cognitive training.

Specific working memory training and transfer of learning. The n-back task as previously discussed is a working memory task that requires the engagement of several processes such as irrelevant target inhibition, ongoing monitoring and updating, as well as task shifting (specifically when engaging in a dual n-back task). Several of these processes are mediated by attentional control including irrelevant target inhibition, and the shifting of attention from old to new stimuli. Attentional control is an important underlying process that is postulated to link the transfer of learning working memory training to improvements in fluid intelligence (Jaeggi et al, 2008; Klingberg 2010). This link is thought to occur through shared neural networks, specifically within the frontal and parietal cortex (Klingberg, 2010). Several studies have investigated the success and validity of the n-back task as a measure of WMC and as a plausible task to improve fluid intelligence (G*f*).

Jaeggi et al. (2008) investigated the time-dependent training effects of an adaptive dual n-back task on transfer of learning to fluid intelligence on healthy university aged students (25.6 +/- 3.3 years of age). The task involved a simple matrix with 8 possible visual and spatial cues and simple letter auditory cues. Participants were randomly assigned either to one of four training groups or one of four control groups. The four training groups differed based on the length of training: 8, 12, 17, or 19 days. Each training group had a matched control group that came to the laboratory for pre and post-outcome measure testing that mirrored the training groups.

The primary outcome measure used by Jaeggi et al (2008) was fluid intelligence, which was assessed using the Raven's Advanced Progressive Matrices (RAPM). To measure for individual differences (during pre-training) and gains (post-training) in WMC both the digit span task, a simple WMC test, and the reading span task (RST), a complex WMC test, were also used. The results showed that improvements in fluid intelligence were dependent on the training dosage, and these gains were most significant after 12 days of training ($F\ (3, 30) = 9.25$; $P < 0.001$). This is a significant finding, suggesting that the dual n-back task is capable of transferring to improvements of G*f*. This finding was later supported by Jaeggi et al. (2011), who demonstrated that fluid intelligence score can be improved in children who train on a dual n-back task (previously discussed).

The results from Jaeggi et al (2008) further demonstrated that the gains on the dual n-back task were related to transfer to the digit span task, however did not significantly relate to transfer to the RST. This finding is significantly relevant to the validity of the dual n-back (to be discussed below). Additionally, the results from Jaeggi et al. (2008) demonstrate that gains in fluid intelligence are not dependent on the improvement of WMC. This was shown by a lack of interaction with the digit span and RST measures at pre and post-test. This finding highlights that there are additional processes, mainly attentional control, that have to link the working memory and G*f* to assist with the transfer for learning. Furthermore, Jaeggi et al. (2008) suggests that the n-back task facilitation of attentional control may in fact be the reason for transfer of learning to fluid intelligence.

Validity of the n-back task. Currently the n-back task is thought of as a complex WMC task, however the findings of Jaeggi et al (2008) which demonstrated transfer of learning to the simple WMC task, the digit span task, but not the reading span task, the complex WMC task, highlights an important question of validity for the n-back task, that is of considerable debate in current research. As the n-back task is considered a complex task, it should demonstrate transfer of learning to the reading span task; however these findings have also been reported in other studies investigating the validity of the n-back task as a measure of WMC (Jaeggi et al., 2010; Kane et al, 2007).

Current research of the validity of the n-back task as a WMC measure often demonstrates conflicting evidence for and against its validity. For example, the n-back task has been demonstrated to highly correlate with the OSPAN task (Shelton, Metzger, & Elliott, 2007; Shelton et al., 2009), but has also been shown to have very little shared variance with the OSPAN task (Kane et al., 2007). The differences and the wavering debate of the validity of the n-back task as a measure of complex WMC highlight that construction/styles of n-back tasks used by any one researcher seem to differ.

For example, the aforementioned studies (Shelton et al., 2007 & 2009 and Kane et al., 2007) used different styles of n-back tasks, including different stimuli presentation, varying on type of auditory and/or visual stimuli, and load of stimuli from dual or single. These differences highlight that the presentation of the task may influence the validity of the results, and that comparing the validity from one study to another is quite difficult. Interesting, while the aforementioned studies found inconsistent relationships with the n-back task as a WMC measure, it was consistently found to have a significant relationship with G*f*.

Summary

The evidence provided here demonstrates that with consideration to important principles of learning that can be acquired from AVG, perceptual, and motor skill learning, along with knowledge of overlapping cognitive functions, effective cognitive training tools can be developed. Also, the evidence provided demonstrates that transfer of learning can occur during any life stage but there is room for a more thorough understanding of how to enhance the effectiveness of training programs (Jaeggi et al., 2011). Instead, future research, while taking into consideration the all the evidence provided here, should focus on understanding the elements of cognitive training and working memory training that best correlates to transfer of learning, and how those elements can be applied for effective construction of training tools that can be used for healthy individuals during any stage of life, and those with acquired brain injuries or diseases (Jaeggi et al., 2011).

Chapter 3: Methods and Procedures

The study procedures were approved by the Dalhousie Research Ethics Board, project code #2011-2598.

Participants

Twenty-four young adults between the ages of 19 – 30 with no history of head injury, neurological or psychiatric disorders, or learning disabilities were recruited. All participants had normal or corrected-to-normal vision, played less than an hour of video games a day and owned a laptop with an external mouse. A total of three participants did not finish the study, two participants (one from each group) dropped out of the study for personal reasons, one participant (from the N-IGMA group) was withdrawn from participation by the researchers due to a failure to complete the minimum 10 out of 15 at-home training sessions. Data from these three participants were excluded from all analyses. Data from two additional participants, both in the N-IGMA group, were excluded from the final analysis. One of these was excluded due to deliberately ignoring task instructions to inflate performance, and the second was due to software problems, which resulted in the completion of less than 10 at-home training sessions in which less than 80% of the blocks were completed. Data from 19 participants were retained for statistical analysis, 9 (22.1 +/- 2.85 years of age) were in the N-IGMA group and 10 (21.7 +/-2.1 years of age) were in the Blockmaster group.

The targeted sample size for this study was thirty participants, fifteen in each group. Similar sample sizes have been used and demonstrated significant effects in related outcome measures, including Clouter (2013), who had eighteen in an experimental and eighteen in an active control group. Likewise, Jaeggi et al., (2008), who had four different experimental groups, had an average group sample size of 18.25. The targeted sample size could not be achieved in the timeframe of this M.Sc. thesis project despite the best efforts of the investigator.

During the initial screening, participants were asked to estimate the number of hours they spent per week during the last six months using a computer, and playing video games. Participants in the N-IGMA group reported spending significantly more ($t(16) = 2.18$, $p < 0.05$) time using the computer (31.1 +/- 14.26 hours/week) than the Blockmaster group (19.0 +/- 6.58 hours/week). Both groups reported spending a similar amount of time per week playing video games; the N-IGMA group reported 1.56 +/- 2.15 hour/week and the Blockmaster group reported 1.28 +/-1.51 hours/week (for a list and count of the self-reported video games played see Appendix J). Participants were given a choice of course credits in combination with financial compensation or just financial compensation.

Equipment

Most outcome measures, including the Stroop, OSPAN task, SymSpan, and the MoveSpan task, were performed on a 27 inch iMac OS10.7, in the Cognitive Health and Recovery Research Lab at Dalhousie University. Participants sat comfortably centered relative to the computer screen and used the keyboard to respond with 'y' for yes and 'n' for no during the OSPAN mathematical equations, and SymSpan judgments. Participants used the arrow keys, which had red, green, and blue stickers on them, to correspond with colour responses for the Stroop trials. The same computer was also used for the training tutorial for the N-IGMA participants. The Stroop task, OSPAN, SymSpan and the

MoveSpan, were all programmed and run from the experiment builder program PsychoPy (version 1.71.01).

Participants used their own laptop and external mouse to access the website for the computer training activities. Once participants in the N-IGMA group finished the training tutorial they completed the rest of the initial training session on their own laptop, as well as the at-home training sessions. Participants in the Blockmaster group used their own laptops for all of the initial training session as well as all of the at-home training sessions.

Procedure

The study included three phases: the pre-training phase, the training phase, and the post-training phase. In the pre-training phase, participants were randomly assigned to either the N-IGMA or Blockmaster group using a table of random numbers. Upon arrival to the laboratory the participants were greeted by their assessor, who was blinded to the participant group assignment. The assessors went through the informed consent (see Appendix H for a copy of the Informed Consent) with the participants and administered a self-reported screening questionnaire (see Appendix A for a copy of the self-reported screening form). Following the self-reported screening questionnaire the assessors administered the outcome measures in the same order for all participants, which was also used during the post-training phase: CFIT, the Stroop task, the OSPAN, the SymSpan, and lastly the MoveSpan.

Following the completion of the MoveSpan, the assessor left the room and the trainer entered. The trainer then guided the participants through tutorials for their assigned computer activities. Participants in the N-IGMA group began their training session on the laboratory computer, and then once they completed the N-IGMA tutorial were instructed to setup their laptop and external mouse. Following this, participants were asked to sign into the website, and bookmark the website for ease of future access. Once on the website participants were given their log-in and password to access the N-IGMA. Once they logged in they proceeded to complete two or three blocks of practice on their own laptop. The number of blocks the participant completed on their own laptop was a subjective decision made by the trainer depending on the amount of time remaining in the training session and the participants' success with the program. Likewise, participants in the Blockmaster group were instructed by the trainer to set up their laptops with their external mouse. Next the participants were asked to sign into the website, and bookmark the website for ease of future access. Once logged into Blockmaster trainers lead a tutorial to introduce the participant to the game, and then the participants completed all five blocks. Participants in the Blockmaster group completed all five, five-minute blocks of their activity. Participants in the Blockmaster group completed all five blocks of the activity during the training session as it takes a similar length of time to complete as it takes participants to learn the N-IGMA, thus minimizing any influence on the assessors ability to guess the activity assigned to the participant.

In the training phase, participants trained on their assigned activity at-home for three weeks for a total of 15 sessions. For each training session participants in the N-IGMA group completed 20 blocks of 20 +n trials of the N-IGMA, which took approximately 25-30 minutes. Likewise, for each training session participants in the Blockmaster group completed five, five-minute rounds of Blockmaster which took approximately 25 minutes. Computerized feedback was provided to the participants as a function of each activity, described in the Computer Activity section below.

During the three week training phase, the trainers provided emails of encouragement and reminders, in addition to responding to any questions the participants might have had. The emails served as a way to keep the participants motivated, and to remind the participants in the N-IGMA group of when the stimulus set was changing, described in the Computer Activity section below. After the pre-training session the participant returned to the laboratory for the post-training assessments. If participants were unable to complete a minimum of 10 out of 15 at-home training sessions, they were excused from the study by the researcher and not invited to return to the lab for the final post-training assessment. Participants who were excused from participation received compensation for all the phase 1 and any training sessions completed.

During the post-training phase, the assessor greeted the participant, and stressed to the participant not to tell them which activity they completed, thereby ensuring assessor blinding. Next, the assessor administered the outcome measures in the same order as in the pre-training assessment. Once the outcome measures were completed, the trainer entered the testing room, provided the participant with appropriate compensation, and thanked them for their time. If participants were unable to attend their scheduled post-assessment date, they were able to reschedule, within one week of the originally set post-assessment date.

The pre-training and post-training assessments were both administered at the same time of day and by the same assessor. The same trainer who gave the tutorial in the pre-training session was responsible for maintaining contact with the participant. The trainers had standard email messages (see Appendix I for examples of the trainer email messages), which were used ensure that each participant received similar contact during their training.

Outcome Measures

There were five outcome measures, four of which (the CFIT, the OSPAN, the SymSpan, and Stroop task) were used by Clouter (2013). The fifth outcome measure (the MoveSpan) was unique to the current study.

CFIT. The CFIT Scale 3, a fluid intelligence test, took approximately 20 minutes to complete. The test was administered following the standardized testing protocol (Cattell, 1971; Cattell & Cattell, 1973). Psychometric testing has shown that the CFIT targets a general factor of intelligence similar to other fluid intelligence tests such as the Raven's progressive matrices fluid intelligence test, attesting to the validity of the CFIT to measure fluid intelligence (Conway et al., 2002). Participants completed Form A during pre-training and Form B during post-training, which is standard protocol for the test.

This test consisted of 4 timed subtests, each completed using pen and paper. Test one was a progressive series, which required participants to recognize the rule for a series of three images containing figures or shapes, and then choose one of six possible images that completes the series. Test two was a classification test, which required participants to determine the relationship among five figures or shapes and choose two which differed from the other three. Test three was a progressive matrices test, where participants were required to find the rule which explains the relationship between the figures or shapes in the matrix, and choose one of six possible images that completes a matrix (the matrix may have contain four or nine boxes with one empty box). The fourth test was a topological conditions subtest, where participants were presented with an image that contains shapes (circles and squares), lines and a single dot, and they must choose one of five possible options in which the dot could be placed in the same relationship as it is seen in the initial image (see Appendix C for an example of the subtests). Each test measured the participant's ability to think abstractly and solve novel problems.

Each subtest has a pre-determined time cap. Test one is 3 minutes, test two is 4 minutes, test three is 3 minutes and test four is 2.5 minutes. The assessor was responsible for monitoring time and ensuring that the participant did not exceed the time cap. Participants were instructed to stop and put their pencils down when the time cap had been reached. Participants were not allowed to make any additional answers once asked to stop.

The Stroop task. The Stroop task, originally designed by Stroop in 1935, is used to investigate selective attention, as it requires maintenance of a goal and inhibition of competing stimuli (Kane & Engle, 2003). The task has since been deemed a valid and reliable measure of executive functions (Van der Elst, Van Boxtel, Van Breukelen & Jolles, 2006). The proportion of congruent and incongruent trials used in the current study matches that used by Kane & Engle (2003). These authors found that performance under such conditions correlated well with working memory measures, and is thus appropriate for targeting executive functioning and task-goal maintenance. During the Stroop task, the participant was comfortably seated at the computer, with the lights dimmed as low as possible. The Stroop task required the participant to indicate the colour of the font used to display words that were colour names. Three words were used: ‘red’, ‘blue’, and ‘green’ (see Appendix F for an example of the Stroop task). The words were presented in congruent colours 80% of the time (48 trials for ‘blue’ and ‘green’ and 49 trials for ‘red’) and incongruent colours 20% of the time (12 trials; 6 trials in each of the two incongruent colours), for a total of 181 trials. Participants were required to identify the colour by pressing the appropriately labeled arrow key (left, down, and right). The task began with 10 practice trials. The Stroop task took approximately 12 minutes. Data recorded for the Stroop task included response time and accuracy of response for each trial.

The Operation Span (OSPAN) task. The OSPAN was originally designed by Turner and Engle in 1989 and is one of the more common measures of complex verbal working memory capacity. The OSPAN required participants to solve mathematical problems presented on the screen while remembering unrelated words. This test is reliable, with high internal consistency, test-retest reliability and test stability (Klein & Fiss, 1999). The goal of this task was to assess verbal working memory capacity in the presence of distracting or interfering verbal information. This task is argued to measure the capacity of the phonological loop of the working memory system. Each trial began by presenting the participants with a mathematical problem in the form of a question; for example, “is (7 * 2) – 1 = 14?” They were required to read the question out loud and respond with “yes” or “no” out loud and by pressing ‘y’ or ‘n’ buttons on the keyboard. Half of the equations were programmed to be correct. Following a single mathematic question, the participants were presented with a new screen image for 1 second that contained a word, which they were asked in advance to read out loud and remember for later recall. There was a 0.5 second delay between the disappearance of the word and the appearance of a new mathematical question. When the trial was complete, participants were instructed to recall, in order and out loud, the words that had been presented (see Appendix D for an example of the OSPAN task). There were 2, 3, 4, or 5 words given before the recall instruction, the blocks of words are referred to as set sizes; e.g., 2 words to be recalled is a set size of 2, while 3 words to be recalled is a set size of 3. There were a total of 42 trials in 12 blocks, which began with 2 additional blocks of practice trials. The set sizes were presented in pseudorandom order with 3 blocks for each set size (following the same protocol as Clouter, 2013). The test took approximately 12 minutes.

For recall and scoring procedures, participants were instructed to recall the words in order and out loud at the end of each block. The participants were instructed if they were unable to remember a word to respond with “I can’t remember or I don’t know” in place of the word they had forgotten. This protocol ensures they remember the words in the correct order and were able to receive full points for the set size. The assessor scored, on an answer key, whether the words recalled were correct and in order. The test was scored based on the total number of the words correctly recalled for each set size. Different word lists were presented at pre-training and post-training.

The Symmetry Span (SymSpan) task. The SymSpan task is also a complex working memory task, which targets visual span capacity (Kane et al., 2004). The SymSpan has demonstrated high test-retest reliability as well as construct and criterion related validity (Redick et al., 2012). For this task, participants were required to remember for recall purposes the specific location of a red square on in a 4 X 4 matrix while performing symmetry judgments. Each trial began by presented an 8 X 8 matrix in which participant were required to make a symmetry judgement about whether the right and left halves of the matrix were mirror images of each other. They respond by pressing "y" for yes or "n" for no on the keyboard. After their response there was a 0.5 second delay before they were presented with a new screen which showed a 4 X 4 matrix in which one of the 16 squares was red and the other 15 squares were white (see Appendix E for an example of the symmetry task). Participants were asked to remember the location of the red square for later recall. The to-be-remembered matrix is presented for 1 second followed by a 0.5 second delay until the onset of the next judgement task. Similar to the OSPAN, there were two, three, four, or five matrices with red squares to-be-remembered shown before the recall instruction, the blocks of red squares are again referred to as set sizes, e.g. two red squares to be recalled is a set size of two, while three red squares to be recalled is a set size of three. There were a total of 42 trials and 12 blocks, which began with two blocks of practice trials. The set sizes were presented in pseudorandom order with three blocks for each set size (following the same protocol as Clouter, 2013). For recall, participants were given an answer sheet with 12 columns of five empty 4 X 4 matrices (the maximum set size is five). Participants were asked to fill in on the answer sheet the locations the red squares in the order they appeared. This test took approximately 12 minutes.

Scores were calculated based on the correct number of remembered locations. When a participant was unable to remember a location, they were told they may skip the corresponding matrix on the answer sheet, to ensure they placed the red squares in the correct order.

The MoveSpan task. The MoveSpan task was used to assess the capacity of working memory for observed actions. This is a task designed for this study which has yet to be analyzed for validity and reliability. The task required participants to perform simple reaching movements while remembering a list of to-be-recalled actions. During the task participants were asked to stand with the palms of their hands facing their body, and informed this was their starting position. Participants were given instructions on the computer screen such as ‘touch your left shoulder with your right hand’ which they were to read out loud and then perform, subsequently returning to the starting position. Participants were told they were not required to remember the reaching movements. Next the assessor triggered the computer to display a to-be-remembered action, which was demonstrated by an animated avatar facing toward the participant on the screen (see Appendix G for example of the MoveSpan). The avatar appeared on the screen for approximately 1 second. Participants were instructed to remember the avatar’s action for later reproduction as though the avatar was representing their own body as seen in a mirror; i.e., if the avatar lifted the right arm to 90^0 of abduction, the participant was required later to lift their left arm. After the avatar completed the action there was a 0.5 second delay followed by another set of reaching movements to perform and so on until the participants were given recall instructions. Once they were given the recall instructions participants were required to physically replicate the avatar actions they have seen. There were two, three, four, or five avatar actions given before the recall instruction with a total of 42 trials and 12 blocks, with two additional blocks of practice at the beginning, the same as the OSPAN and the SymSpan. There were a total of 14 different avatar actions which were pseudo-randomly distributed between the 12 blocks; due to a limited number of avatar action video clips, each movement is repeated three times within the experimental trials (Wood, 2007). There were no repeating reaching movement instructions. The assessor recorded on an answer sheet whether the participant performed the correct reaching movement as well as the whether the action performed was correct. To receive a point, the participant must have physically replicated the correct action on the correct side of the body. The test took approximately 12 minutes to perform.

Computer Training Activities

The computer activities used for training were performed on the participant's own laptop. The activities included a custom dual n-back working memory task called the N-IGMA (experimental group), and a visuospatial task devoid of working memory requirements similar to the popular game Tetris, called Blockmaster (active control group). For both activities the participants could pause and take a break at any time, although they were encouraged to complete the activity unbroken start to finish. Participants were also encouraged to minimize any distractions in their surrounding environment by turning cell phone ringers off and by not watching TV or listening to music. Participants were required to use an external mouse to interact with the computer games, which eliminated any variability due to the different visuomotor demands of input devices such as keyboards or touchscreens.

Experimental group task. The N-IGMA, the experimental task, is a custom designed dual n-back task that includes the principles of adaptive difficulty, motivation, feedback and repetition. It is a dual task because visual and auditory stimuli are presented simultaneously. Participants were required to watch and listen to a sequence of stimuli, and respond when the current auditory or visual stimulus matched the stimulus presented "n" items previously within the same sensory modality. Participants were given a new set of visual stimuli and auditory stimuli at the beginning of each week, similar to Jaeggi et al. (2011), who also changed their stimuli weekly to encourage motivation. During week one, the visual cues were blue triangles with letters as auditory cues. The letter auditory stimuli consist of letters that were known to be phonologically distinct. Letters that are phonologically different from each other were used as they demonstrate less error rate when recalling sequences of letters than letters that sound similar (Baddeley, 2003). In week two participants saw images of a lighthouse in which the position of the lighthouse changed and they listened to numeric auditory cues. Week three consisted of landscape images as visual cues and words from the phonetic alphabet as auditory cues.

Participants started at an N=1 level and could progress up to N=6 depending upon performance. Each day they began at the level they achieved during the previous session except when the stimuli were changed at the start of a new week, in which case the N-level was returned to 1. Participants were informed by email from the trainer before the change in stimuli and reminded they would return to N=1 automatically by the program. As mentioned earlier, the purpose of changing the stimuli was to maintain interest and participant engagement.

The N-IGMA consists of 20 blocks of 20 + N trials, where each individual block were performed at a specific N-level. Progression to a higher N-level or regression to a lower N-level occurred only after the completion of a block. An adaptive algorithm built into the program was set to advance participants to the next N-level if they achieved a combined (auditory and visual) score of 80% after one block, and to regress participants to the previous N-level if they scored less than 50% (combined auditory and visual) per block on three consecutive blocks. Participants stayed at the same N-level if their performance ranged between 50% and 80%. At the end of each block the participant was shown their percentage score, thus receiving summary feedback for the entire block. During the initial training session participants were taught the purpose and meaning of the percentage score seen at the end of each block. Additionally, participants received immediate feedback on the accuracy of each response, through a visual change on the screen corresponding to the visual or auditory channel of the N-IGMA display. Participants were able to pause at any point but were encouraged to finish the activity without taking any breaks.

The data recorded include correct matches, false alarms (responses when match is not present), response times for correct matches, and N-level achieved per session. Each N-IMGA session was expected to take 25 - 30 minutes to complete and could be completed at any time throughout the day the participant wished, although it was suggested they complete the activity at approximately the same time every day. Once participants completed their daily activity, the program prevented them from logging in again until the following day. This prevented participants from trying to complete several sessions of training all on the same day, helping to control the duration over which the training took place.

The active control task. The active control activity known as Blockmaster is a spatial task that required participants to rotate and fit together, like puzzle pieces, four geometric shapes (blocks) as they 'fell' toward the bottom of the computer screen, with the goal of aligning the bottom edges of the shapes to fill complete horizontal lines without gaps. Blockmaster was created to be a non-adaptive version of the popular game Tetris, in the sense that the speed of the game remained constant despite performance or elapsed time. Tetris has been used previously as an active control task because it requires visuospatial attention and visuomotor control, but not working memory or other more complex forms of attention; as such, this task controls for the interactive game-like characteristics of the N-IGMA training task minus the key features of working memory and adaptive progression (Green & Bavelier, 2003, Nouchi et al. 2012).

The task included five blocks of 5 minutes, at the end of each block of 5 minutes the screen reset, cleared, and participants started the following block with no blocks or lines in the playing area. The scoring for Blockmaster was set so that for each horizontal line cleared the participant received a set amount of points: one line was 40 points, two simultaneous lines were 100, three simultaneous lines were 300 and four simultaneous lines were 1200 points. Like the N-IGMA, participants were able to pause at any point but were encouraged to finish the activity without taking any breaks. Feedback provided to each participant for each session included the number of lines cleared, round score (for the most recent block), total score (score across all blocks for that day), and the High Total score (highest scoring block ever completed), all of which were recorded by the program. At the end of each block the participants were shown a list with each round score completed during that session to that point, which was intended to serve as motivation for participants to beat their previous score.

Statistical Analyses

This was a mixed design study with one between-subjects factor (training group: N-IGMA and blockmaster), and one within-subjects factor (time: pre-training and post-training) for the primary outcome measures. Thus, these measures were analyzed using separate mixed ANOVAs (group by phase). Outcome measures included scores for each of the four individual CFIT subtests (series, classification, matrices, conditions) and the combined, overall score. For the Stroop test, outcome measures included response times and average error percentages for congruent and incongruent trials, in addition to the response time and error percentage interference effects (the difference between the response times or error percentages for incongruent and congruent trials). For the three WMC tests (OSPAN, SymSpan, and the MoveSpan), outcome measures included scores for set size (number of items to-be-remembered) two, three, four and five, as well as the total overall scores which included set sizes two-five.

To investigate the relationship between training effects (measured on the training activities over the course of the training sessions) and improvements on the various outcome measures, each individual's performance on the training task was fit with a linear function relating training session (1-15) and average daily N-level for both the N-IGMA and the Blockmaster group. From these linear fits, slope (rate of improvement) and y-intercept values (estimated starting ability) were extracted. The slope and the y-intercept values were then compared to the change scores for each outcome measures. Change scores were calculated as post-training scores minus pre-training scores for each outcome measure.

To determine if changes in outcome measures were related to the individual's initial level of fluid intelligence, correlations were computed for each outcome measure change score versus each individual's pre-assessment CFIT score for both the N-IGMA and Blockmaster groups.

To investigate the relationship between the MoveSpan, SymSpan, and OSPAN tasks, three different sets of correlations were calculated. First, to determine the amount of variance shared between the three tests prior to the intervention, correlations between all pairs of tests were computed using pre-training scores (overall scores for spans two-five). Second, to determine if improvements in the various types of working memory over the training sessions were related to each other, correlations were computed between all pairs of tests using post-pre difference scores (overall scores for spans two-five). Finally, to evaluate the variance shared between working memory tests after training was complete, correlations were computed for all pairs of tests using post-training scores.

Data analysis was completed using the statistical program SPSS. The alpha for the current study was set at 0.10 for each of the four hypotheses. This liberal type I error criterion was selected because the study was slightly underpowered given that recruitment targets were not achieved. The critical p-value was then adjusted using Bonferroni adjustment to account for the multiple comparisons made within each hypothesis. After Bonferroni adjustment the critical p-value for the first hypothesis was $p=0.004$; the second hypothesis was 0.004; the third hypothesis was 0.002; and the fourth hypothesis was 0.01. Statistical tests with a p-value between the critical p and 0.05 were viewed as interesting and discussed as meaningful trends. Due to the small sample size, outlier participants were not removed.

Chapter 4: Results

Computer Activity Training Performance

The participants in the N-IGMA group completed an average of 14.2(+/- 0.63) at-home training sessions (min = 13, max = 15). The participants in the Blockmaster group completed an average of 14.6 (+/- 0.66) at-home training sessions (min = 13, max = 15).

The results indicate that both training groups improved at the trained task across the at-home training sessions. Analysis of training performance changes over the course of the at-home training sessions were conducted by fitting a linear regression to the average daily N-level achieved in the N-IGMA, and the average daily score for the Blockmaster groups. The results of the regression analysis indicate improvements in performance in the N-IGMA group as b_1=.114, p<0.001 (R^2=.168, F(1, 126) = 25.44, p<0.001). The improvements in the average daily N-level achieved over the at-home training sessions can be seen in Figure 1. The regression analysis indicates improvements in performance in the blockmaster group as b_1= 121.43, p<0.001 (R^2=.314, F(1, 145) = 15.71 p<0.001), the average daily score achieved over the at-home training sessions can be seen in Figure 2.

Outcome Measures: Analyses of Group Differences Pre- and Post-training

The primary hypothesis for this study was that improvements in all outcome measures would be observed for the N-IGMA group (post-training minus pre-training), and that these improvements would exceed those in the Blockmaster group, manifesting as a significant group x time interaction. This hypothesis was evaluated using separate mixed 2 x 2 ANOVAs with one between-subjects factor (training group: N-IGMA and

Blockmaster), and one within-subjects factor (time: pre-training and post-training) for each of the outcome measures. Evidence in support of the hypothesis would come in the form of a significant Group x Time interaction matching the described pattern. Descriptive statistics and the results for each ANOVA, for all outcome measures, are shown in Table 1. In general, the results of these ANOVAs do not provide support for the interaction hypothesis. Significant findings and meaningful trends are reported below.

CFIT. There were five ANOVAs completed for the CFIT, one for each of the four subtests, and one for the overall combined scores from all the subtests. The ANOVAs revealed a significant main effect of time for CFIT "classification" subtest two, $F(1,17) = 64.42$, $p < 0.001$, Figure 3. A significant main effect of time (post-training better than pre-training) was found for CFIT "conditions" subtest four, $F(1,17) = 36.80$, $p < 0.001$, and a significant main effect of group (N-IGMA group showed overall higher scores than the Blockmaster group) was identified for subtest 4, $F(1,17) = 9.50$, $p < 0.007$, Figure 4. A significant main effect of time was found for the overall CFIT score, $F(1,17) = 79.40$, $p < 0.001$, shown in Figure 5.

The OSPAN Task. For the OSPAN, five ANOVAs were completed, one for each set size (2-5) and one for the overall score. The ANOVAs revealed trends for the main effect of time for the set size four, $F(1, 17) = 7.70$, $p = 0.01$, and also for the overall OSPAN score, $F(1, 17) = 8.33$, $p = 0.01$. As seen in Figures 6 and 7, both groups improved their scores on set size four and the overall measure from pre- to post- training. There were no significant main effects or interactions for set size five.

The SymSpan task. For the SymSpan, five ANOVAs were completed, one for each set size (2-5) and one for the overall score. There were no significant main effects or interactions for the SymSpan task. The overall SymSpan score suggested that both groups improved from pre- to post-training, however this did not reach significance $F(1,17) = 3.32$, $p=0.086$.

The MoveSpan task. For the MoveSpan, five ANOVAs were completed, one for each set size (2-5) and one for the overall score. There was a trend for a time main effect for set size four, $F(1,17) = 4.56$, $p=0.048$. Unexpectedly, this main effect indicated that participants in both groups decreased their scores at post-training, Figure 8.

The Stroop task. For the Stroop task ANOVA's were completed for the error rate interference and the error rates for congruent and the incongruent trials analyzed separately. There were no significant main effects or interactions for the error rate interference. A trend for a group by time interaction was revealed for error rate in the incongruent trials, $F(1,16) = 4.80$ $p<0.043$. As seen in Figure 9, participants in the N-IGMA group increased their error rate post-training for incongruent trials, whereas the Blockmaster group decreased their errors. No significant effects were found for error rate in the congruent trials.

There were also ANOVA's completed for the response time interference effects and the response times for the congruent and the incongruent trials analyzed separately. There were no significant main effects or interactions for either the response time interference effects or for congruent and incongruent response times.

Individual Differences: Association between Improvements on the Trained Task and Outcome Measures

The second hypothesis for the study stated that improvements in outcome measures would be correlated with improvements in the trained task (N-IGMA). However, since there was little evidence that outcome measures improved more for the N-IGMA than the Blockmaster group; the hypothesis was extended to both training groups. To test these hypotheses for the two groups, correlation coefficients were calculated for individual training performance changes over time (i.e., the slope for training task performance versus training session) versus outcome change scores (post-training minus pre-training) for all measures. The descriptive statistics for the change scores of each group are shown in Table 6. The results of all the correlations regarding the slope of average daily scores are shown in Table 2 for N-IGMA and Table 3 for Blockmaster.

Individual differences: Initial Fluid Intelligence as a Predictor of Outcome Measure Changes

The third hypothesis was that improvements in outcome measures would be greater for participants who demonstrate higher initial CFIT scores in the N-IGMA group. This hypothesis was tested by computing correlations between pre-training CFIT scores and change scores for each outcome measures separately for the N-IGMA (Table 7). There were significant correlations seen in the N-IGMA group.

The pre-training CFIT scores correlated with the change in the overall OSPAN scores ($r = .848$ p=0.004) and response time interference effects ($r = .749$, p=0.02), in the

N-IGMA group, however both are only considered meaningful trends. When response time interference effects were separated into congruent and incongruent response times there were no additional significant findings or trends.

To further explore the influence of individual differences of initial fluid intelligence on change in the outcome measures the Blockmaster group was also analyzed. However, unlike the N-IGMA group, there were no significant correlations in the Blockmaster group (Table 8).

Individual differences: Starting level on the training task as a predictor of changes in the outcome measures

To further explore individual differences and how they may predict changes in the outcome measures, the starting N-level participants began their at-home training sessions on were correlated with the change scores of the outcome measures. The starting N-level was calculated as the y-intercept of the average daily N-level achieved per participant for the N-IGMA group, providing an estimate of the performance on the first day of training. There were no significant findings for the N-IGMA group as shown in Table 4.

The starting level on Blockmaster was also correlated with the change scores of the outcome measure to determine if starting level in Blockmaster relates to any changes in the outcome measures. The starting level participant began their training sessions in Blockmaster was calculated as the y-intercept of the average daily high scores of the all the training sessions. Unlike the starting N-level of the N-IGMA, there was a strong positive correlation between the y-intercept and the overall change in the SymSpan task

($r = .846$, $p = .002$, seen in Figure 10), and with a meaningful trend in the overall change in the MoveSpan task ($r = .717$, $p = .019$, seen in Figure 11), as shown in Table 5.

Working Memory for Observed Actions

The last hypothesis was that the measures of the MoveSpan measures will be correlated to the SymSpan task measures but not to those of the OSPAN. The hypothesis was tested by performing correlations first to compare the pre-training overall scores for the MoveSpan to the SymSpan task and the OSPAN. Secondly, correlations were then used to compare the change scores for the MoveSpan to the SymSpan task and the OSPAN.

The pre-assessment scores for the MoveSpan task and the SymSpan task demonstrated a positively correlated trend $r = .468$, $p = .043$ as shown in Table 9. The MoveSpan and OSPAN were not significantly correlated. There were no significant results for the change scores seen in Table 10. The post-training scores for the MoveSpan and the SymSpan were significantly correlated $r = .675$ $p = .002$, the MoveSpan and the OSPAN were significantly correlated $r = .695$, $p = .001$. The post-training scores are shown in Table 11.

There were no additional significant results for either the pre-training, change, or post-training scores when set size four and five were analyzed separate from set size 2 and 3, only the overall scores revealed any significant findings.

Chapter 5: Discussion

There were three goals for the current study: first, to provide further evidence for transfer of learning effects from working memory training; second, to determine if our custom-designed working memory training game, known as the N-IGMA has efficacy compared to an active control condition; third, to explore the properties of working memory for observed action in relation to other working memory domains. The hypotheses were (1) compared to the active control group, the experimental group (N-IGMA group) will exhibit significantly higher improvements of scores on all outcome measures including fluid intelligence measured by the CFIT, attentional control measured by the Stroop task, and working memory span measured by the OSPAN, SymSpan, and MoveSpan task; (2) the improvement of scores on the outcome measures will be correlated with improvements on the training tasks in the N-IGMA group; (3) the increase of scores on the outcome measures will improve more with participants who demonstrate higher CFIT scores during pre-training than those with lower CFIT scores; (4) the change in scores of the MoveSpan between pre-training and post-training will be correlated with the change in scores of the SymSpan task but not with the scores of the OSPAN task.

Both the N-IGMA and the Blockmaster groups improved at their respective training task over the course of the 15 training sessions, confirming engagement in the task and attention to instructions. However, there was little evidence to support the first and second hypothesis. In the outcome measures that showed significant change from pre-test to post-test, the differences were equivalent for the N-IGMA and Blockmaster groups, and furthermore the degree of improvement on the training task was unrelated to changes in the outcome measures. There is little evidence to support the third hypothesis that individuals who exhibit higher initial fluid intelligence scores would improve their scores on the outcome measures more than those with lower initial fluid intelligences scores. There is some evidence to support the fourth hypothesis that the MoveSpan task overlaps to some extent with the SymSpan task.

The results from this study show little evidence that playing the N-IGMA is superior to an active control task (Blockmaster) at facilitating transfer of learning effects to fluid intelligence. The CFIT scores used to measure fluid intelligence include four subtests, only two of which demonstrated meaningful trends and significant post-training effects (subtest two, classification, and subtest four, conditions) in addition to the overall CFIT score. As well, there was a meaningful trend for a group main effect seen for CFIT subtests four, showing that participants in the N-IGMA group had higher pre- and post-training scores than the Blockmaster group (Table 1) but there was no interaction.

The results of CFIT subtest four were similar to those of Clouter (2013), which is the only other study to have used the CFIT to measure the effects of working memory training. Clouter demonstrated that training on an n-back task for three weeks while staying at an N=1 level (active control group), or progressing to new N-levels based on performance (experimental group) both led to significant improvements on the CFIT subtest four. It was postulated by Clouter that these improvements may either be due to test-retest effects or an overlapping cognitive system may be used for both the N-back task and CFIT condition subtest four. This would suggest that the mere engagement of working memory is sufficient to produce gains on this CFIT subtest, and that continuous increases in difficulty are not necessary. Other research supports this idea, suggesting that the dual adaptive n-back task may not be necessary to influence aspects of fluid intelligence (Jaeggi et al., 2010). However, the significant time main effect found in the present study may suggest the test is also sensitive to test-retest effects.

The non-significant main effects and interaction for CFIT subtest three (matrices) is opposite to the findings of Clouter (2013), who demonstrated significant improvements in participants who played the adaptive dual n-back task but not a non-adaptive dual n-back task. Furthermore, the present findings are inconsistent with other previous research which demonstrate that N-back training facilitated transfer of learning improvements in matrix-like fluid intelligence tasks (Raven's Advanced Progression Matrices and the Bouchumer Matrices) – tasks thought to evoke the same inductive reasoning for spatial relationships as required for the CFIT subtest three (Jaeggi et al., 2008; Jaeggi et al., 2010; Jaeggi et al., 2011). The reason for this difference is currently unknown.

The results for the OSPAN task also provide little evidence the N-IGMA was superior to Blockmaster at facilitating transfer of learning effects to verbal working memory since performance improved for both groups. It is speculated that the improvements seen in both groups might reflect simple test-retest effects and not transfer of learning from either task. Previous research investigating the reliability of the OSPAN by Klein & Fiss (1999) found significant improvements of the participants scores between testing time one and time two, separated by three weeks, but no difference from testing time two and time three which occurred six-seven week apart. Klein & Fiss (1999) attributed these improvements between time one and time two to have occurred to test-retest effects.

An alternative possibility to the test/retest hypothesis is that verbal working memory benefits from equivalent transfer of learning effects from both Blockmaster and N-IGMA training. This possibility seems unlikely; however, given that the OSPAN is a test of verbal working memory and Blockmaster is a visuospatial task that involves little if any working memory. Thus, the current findings appear to indicate that the OSPAN is sensitive to test/retest effects, at least in this young population, and that N-back training does not facilitate transfer of learning effects to this particular test (Jaeggi et al., 2008; Jaeggi et al., 2010; Kane et al., 2007).

Jaeggi et al. (2010) found that university-aged participants trained using an N-back task did not demonstrate transfer of learning to the OSPAN task despite improvements to measures of fluid intelligence. They speculated that although both N-back task and the OSPAN are complex working memory tasks, the tasks have been shown to demonstrate little common variance (Jaeggi et al., 2010; Kane et al., 2007). This could be because N-back tasks require attention for relevant and irrelevant stimuli; recognition and familiarity based responding and processing, whereas the OSPAN requires more active recall, and attentional filtering and recognition (Jaeggi et al., 2010; Kane et al., 2007). Furthermore, the N-back task requires addition and deletion of information from working memory whereas the OSPAN task requires only maintenance of information in the face of distraction. This suggests that further research interested in improving verbal WMC should explore other methods of training, as well as other verbal WMC tests which may be less sensitive to test/retest effects. If the OSPAN is used, it may be advisable to perform two baseline assessments so that test/retest effects plateau prior to the training intervention (Klein & Fiss, 1999).

The non-significant effects seen with the SymSpan task support the findings by Clouter (2013), who also did not see any significant transfer of learning effects from the N-back task to visuospatial working memory. This may suggest there is no overlap in the cognitive systems used in the N-back task and spatial working memory, although both the Brain Workshop used by Clouter, and the N-IGMA used here have visuospatial cues which are expected to require the visuospatial working memory system. Both the current and Clouter's studies use the same visuospatial working memory test, the SymSpan task, thus it is possible that this task is not tapping into the same type of spatial working memory that is trained with N-back tasks.

It has been long postulated that attention is the underlying mechanism that connects working memory and fluid intelligence, acting as a portal for transfer of learning effects (Jaeggi et al 2011; Klingberg, 2010; Kane & Engle, 2003). Attention control is considered a role of the central executive (a component of working memory), and it is required during the Stroop task for task-goal maintenance, and filtering goal-relevant (font colour) and irrelevant information (word) (Baddeley, 2003; Baddeley, 2000; Conway et al., 2002; Kane & Engle, 2003). The results of the current study show no changes in the Stroop task reaction time interference effects and unexplainable changes for error interference effect for both groups after training. These findings occur despite the presence of meaningful trends and significant improvements for both groups in other cognitive tests like the CFIT and OSPAN. This pattern is inconsistent with the idea that training on the N-IGMA or Blockmaster task is directly leading to changes in cognitive function, as one would expect that attention measures would change as well. These results provide some support for the earlier contention that the gains in the cognitive measures seen in the current study might simply be due to test/retest effects rather than legitimate changes in cognitive capability.

The goal of transfer of learning is not limited to the cognitive training domains, and it has long been a topic of interest in motor skills learning. But unlike the cognitive training field, in which robust transfer of learning is a consistently stated goal, it is known there are limits for transfer of learning in sport (Magill, 2007). Positive transfer can occur for general domains such as general physiological adaptations (e.g. aerobic capacity) and general ability for decision making but movement or motor skills are often associated with negative transfer to other skills (Baker, Cote & Abernethy, 2003; Magill, 2007). Individuals experience negative transfer, when one motor skill hinders the initial performance of other new skills. For example if an individual who has played tennis for some time, then decided to switch to badminton, will initial experience negative transfer while trying to learn an forehand serve (Magill, 2007). These two motor skills might seem similar, given they are both forehand serves however they require a different action of the wrist which takes time adjust to when switching from one sport to another (Magill, 2007).

Thus, in the motor learning fields there is an understanding of the spectrum of transfer of learning including negative and positive transfer. While in the cognitive research field there seems to be a certain level of expectancy that positive training should be occurring from the training of one cognitive function to another, even though it is not the case in other domains of human behaviours. Transfer of learning in cognitive training research may need to consider negative transfer, and zero transfer, and then devise a spectrum on which transfer of learning may or may not occur.

To forge a transfer of learning spectrum for N-back training, a thorough understanding of the cognitive functions underlying complex task performance is required. The N-back task differs from other complex working memory tasks as it requires recognition, and rapid updating and inhibition of information. In contrast, complex span task such as the OSPAN and reading span task recruit active recall mechanics (Kane et al., 2007; Jaeggi et al., 2010). The difference in cognitive functions required to complete the N-back and other complex span task supports the accumulating evidence that the N-back task shares little variance with complex working memory test such as the OSPAN and RST (Kane et al., 2007; Jaeggi et al., 2010).

Additionally, the N-back task may require greater attentional control than the complex working memory task. For example the N-back requires more attentional control processes for inhibition and interference from competing and irrelevant stimuli. Attentional shifting is required for retrieving stimuli which are no longer in the attentional focus (Jaeggi et al., 2010). The extent of attentional control activation may be more demanding for the N-back than for the complex working memory task, and may underlie the lack of shared variance between the tasks. Additionally the N-back task correlates better to short-term memory than WM, and also correlates to fluid intelligence better than working memory (Jaeggi et al., 2010).

In short, predictions about near and far transfer of learning effects require a comprehensive understanding of the cognitive functions underlying the tasks in question. Based on accumulating evidence related to N-back training, it might be reasonable to place complex working memory span tasks closer to the far end of the transfer spectrum, and short-term memory, fluid intelligence, certain components of attention closer to the near end. It will be important to consider and determine if there are any implications of negative transfer, such as seen in motor skills, from N-back training. Reconsidering this more representative view of transfer of learning with N-back training may transform how to predict the success of transfer of learning to certain cognitive functions.

Investigating Individual Differences: Training Task Performance and Outcome Measure Change

If improvements seen in cognitive tasks occur via transfer of learning from the training task, then it is logical to predict a correlation between the degree of training performance improvements on the N-IGMA and the magnitude of gains in the outcome measures. In contrast to the second hypothesis, no significant correlation was detected between the training performance in the N-IGMA and the changes in the cognitive tasks. This hypothesis was extended to include the Blockmaster group given the observed improvements in outcome measures, but no significant relationship was detected between Blockmaster training gains and changes in the outcome measures. Importantly, the improvements in the training tasks are due to legitimate gains in task performance capability, while any significant time main effect seen in the cognitive tasks shown in the current study are possibly due to test/retest effects, therefore the training task performance gains are not related to changes in the outcome measures. These results support Clouter’s (2013) findings that the performance change in the N-back task was not reflective of changes in the various outcome measures.

However, the above findings differ from those seen by Jaeggi et al. (2011) who found that individual gains on an N-back training task were predictive of transfer of learning effects to fluid intelligence in children. They found when the children's N-back performance was divided into low and high performance gains, only the group with larger gains in training performance demonstrated transfer of learning effects to fluid intelligence, and the participants with lower changes in training performance did not improve fluid intelligence scores. Jaeggi et al. (2011) also reported that initial fluid intelligence scores were independent, not predictive, of the training performance gains. Therefore, participants with the larger performance gains did not start with higher fluid intelligence.

The contradictory findings described above may relate to differences in the ages of the participants in the various studies. Jaeggi et al. (2011) studied children with the average age of 9, while both the current study and Clouter (2013) used university-aged participants. However, Jaeggi et al. (2008) found that training performance gains and the number of training days were predictive of gains in fluid intelligence in a university-aged sample (average age of 25.6). The participants trained using an N-back task for 9, 12, 17, or 19 days for approximately 25 minutes a day. These results suggest the difference between the ability of training performance to predict changes in fluid intelligence may not be a simple artifact of age.

Recently, Au et al. (2014) performed a meta-analysis of twenty studies between 2008 and 2013, which measured transfer of learning to fluid intelligence using the N-back task as a cognitive training tool. An aspect of this analysis examined moderators of successful transfer of learning from the N-back training. They found the parameters of training including starting n-level, training task performance, and session length, did not significantly relate to transfer to fluid intelligence. There were trends for starting level and session length which suggested participants starting at a lower n-level had more to gain in fluid intelligence, and that shorter training sessions result in larger gains in fluid intelligence. They postulate that the latter occurs because shorter sessions are perceived as more attainable, enjoyable, and participants are more motivated to complete them.

An interesting finding from Au et al. (2014) was that monetary compensation demonstrated a negative trend on the success of transfer of learning. This negative trend suggested the more participants who were paid demonstrated less transfer of learning then those who received less compensation. Au et al. (2014) speculated that this negative relationship occurred as a reflection of intrinsic motivation. Therefore, it seems that transfer of learning may be heavily dependent on the participant's motivation and less on their performance on the task itself.

Investigating Individual Differences: Fluid Intelligence and Outcome Measures Changes

Correlational analyses were used to assess the potential influence of individual differences in pre-training fluid intelligence on changes in the various outcome measures. These analyses were performed for both the N-IGMA and Blockmaster groups to better understand the implications for initial fluid intelligence on changes in cognitive functions. While there were some meaningful trends within the N-IGMA group, the initial fluid intelligence of the participants in the Blockmaster group did not predict any changes in the outcome measures. Furthermore, it is also important to note that there were no significant differences between the pre-training overall CFIT scores for N-IGMA and Blockmaster groups, Table 15.

Within the N-IGMA group, initial CFIT scores did not correlate with either the training performance gains, the starting level of the N-IGMA, nor the change in the overall CFIT scores. These findings suggest that pre-training fluid intelligence does not predict success of playing the N-IGMA or transfer of learning effects for fluid intelligence. These general findings that initial fluid intelligence scores do not predict training performance gains are in agreement with the results seen by Jaeggi et al (2008) (discussed earlier) who found training related gains were not reflective of pre-existing individual differences of fluid intelligence.

Individual differences in the pre-training CFIT scores show a positive correlation trend with changes in the OSPAN in the N-IGMA group while there was no correlation with participants in the Blockmaster group, Table 8 and 9. There are two possible reasons for this correlation to have occurred. First, it is possible that participants in the N-IGMA group with higher fluid intelligence were able to improve their verbal working memory by more than those with lower initial fluid intelligence and that this improvement was dependent on the group the participants were in. This may suggest that individuals with higher fluid intelligence may benefit more from training on the N-IGMA in relation to changes in verbal working memory. However, this may only be specific to younger adults and additional speculation should not be made regarding other populations. For example, older adults with high and low fluid intelligence may both benefit from training. Therefore based on the current results and sample population, these findings should not be generalized without further research to specific target populations.

The second possibility for the correlation between the pre-training fluid intelligence and the change in the OSPAN is that individuals with higher pre-training fluid intelligence may find the distractor task easier, thus making the task easier to complete. The distractor task requires participants to complete mathematic equations. If participants with higher fluid intelligence are able to complete the equations with little effort they may not be as distracting as those with lower fluid intelligence. These results highlight the importance of considering individual differences when assessing the success of cognitive training and require further investigation. As mentioned above, other complex verbal working memory span tasks should be considered in future research assessing verbal working memory.

Investigating Individual Differences: Training Task Starting Level and Outcome Measures Changes

To further explore various individual differences that may influence changes in the outcome measures, consideration was given to the starting level on which participants began training for both N-IGMA and Blockmaster. There were no significant correlations between the starting N-level of the N-IGMA and any of the various outcome measures. Interestingly, there were meaningful trends for positive correlations with starting level of Blockmaster and changes in the SymSpan and the MoveSpan task, Table 5. This suggests the better the initial training performance on Blockmaster the more likely participants were to improve components of visuospatial working memory measured by the two tasks.

Blockmaster is a visuospatial task, which requires the implementation of strategy within the visuospatial domain; however, it does not have any direct working memory component. As discussed earlier, this task was chosen for the active control group because it has been used in other similar protocols (Green and Bavelier, 2003; Nouchi et al., 2012). These findings suggest that cognitive functions required for planning and executing visuospatial strategies may overlap with the visuospatial working memory system, and that for this reason Blockmaster and Tetris might not be the best choice for active control groups.

Working Memory for Observed Actions

An exploratory aspect of the current study was to determine if training in a working memory task with verbal and visuospatial information would produce transfer of learning effects for a working memory task using observed actions as stimuli. There is disagreement in the literature as to whether working memory for observed actions is a subcomponent of the visuospatial sketch pad or a separate component of the working memory system (Wood, 2007; Smyth & Pendleton 1989). If working memory for actions and visuospatial information overlap, one would predict a positive correlation between change scores for the SymSpan and MoveSpan tests

First of all, earlier analyses revealed no significant main effect of time or a group x time interaction for MoveSpan scores. Indeed a trend suggested a decrease in MoveSpan performance for the set size of four and the overall MoveSpan mean score from pre- to post-testing for both training groups. There seems to be only one plausible reason for this outcome, given that the task was equally difficult in the pre- and post-testing sessions given the same avatar actions and a random distribution of action sequences in both phases. The decrease in performance at post-testing may reflect a lack of motivation or perhaps fatigue given that MoveSpan was the final task on the final day of the experiment.

To directly assess the hypothesis that the change scores for the MoveSpan would be related to the change scores for the SymSpan, correlations were analyzed; however, the correlation analysis revealed no significant results or trends. To further investigate possible relationships between the WMC tests, correlations for the changes score of the SymSpan were compared to the OSPAN, and the MoveSpan was compared to the OSPAN. The goal was to determine if any of the changes seen in the OSPAN related the changes in either the SymSpan or the MoveSpan. The verbal and the visuospatial working memory systems, though considered separate systems share between 70 – 85% variance (Kane et al., 2004). Therefore, since there were significant changes in the OSPAN and none in either the SymSpan or the MoveSpan there should be no correlations. The correlation in the change scores did not reveal any relationship between the OSPAN and either the SymSpan or the MoveSpan.

Further exploring the relationship between the working memory span tasks, correlations were performed on the overall pre-training scores for each task unlike the previous analyses which focused on pre-post change scores. Interestingly, the correlations on the overall pre-training scores showed a meaningful trend with a positive correlation between the MoveSpan and the SymSpan task, Table14. This relationship could suggest the MoveSpan is targeting, at least in part, the visuospatial sketch pad, the systems targeted by the SymSpan. The correlation between the OSPAN and the MoveSpan did not reveal any clear trend, supporting the likelihood that separate systems were involved in the two tasks. The non-significant correlation between the OSPAN and the MoveSpan suggests the phonological loop was not targeted by the MoveSpan.

Collectively, these correlations provide some validation of the MoveSpan task because the MoveSpan scores were related to a commonly used test of visuospatial sketch pad and not to a test tapping the phonological loop (Kane et al., 2004). The results from the pre-training correlations additionally provide evidence that the SymSpan and the OSPAN target separate working memory systems. This adds support to the working memory model proposed by Baddeley and Hitch for the separate visuospatial and verbal working memory components. Further research is required to validate the MoveSpan as a measure of complex working memory for observed actions.

Future Research

There is a large body of evidence currently available in the cognitive training field, and it is important to start narrowing down the different factors that influence the success of cognitive training. The factors can range from the features of the training game being used to individual differences in initial ability. Future research in working memory training should consider how individual differences such as fluid intelligence and training performance influence the magnitude of transfer of learning effects to other cognitive functions. Considerably more effort should be made to understand the specific cognitive functions required for the performance of specific training tasks and outcome measures given the notion of near versus far transfer of learning. It is possible, as discussed earlier, that even two tests of working memory function may engage quite different processes such as recognition versus retrieval, goal maintenance, and storing versus deleting information

Future research into working memory for observed actions should test the MoveSpan for validity and reliability. It might be worthwhile to determine if improving working memory for observed action could help individuals gain more from motor rehabilitation. As this memory system is important to how we interact and understand our social interactions, it may have significant implications for individuals who experience difficulty in social settings and understanding body language.

While Tetris and its custom-designed relative Blockmaster have been used in previous research as an active control, the current study suggests that these might not be ideal control tasks as they might produce more transfer of learning than anticipated. An ideal active control task should be matched for the time spent interacting with the computer in the experimental group, while not impacting any cognitive functions. It is possible the strategy components of Blockmaster (e.g., positioning blocks in such a way to permit the maximum accumulation of points when a specific shape appears) may require enough cognitive functions to influence transfer of learning if played consistently enough.

Limitations and Delimitations

The significant limitation of the current study was the small sample size, with a total of 19 participants included in the data analysis, 9 in the N-IGMA and 10 in Blockmaster. More participants would have given the analyses greater statistical power. A delimitation of the study was the population used. The participants recruited were healthy young adults between the ages of 19 – 30 with no indication of cognitive difficulties; as such, the range of cognitive capabilities was relatively narrow, possibly restricting the potential to detect significant correlations. All of the participants were students with the exception of two. It is possible that this age limit and the sample population, being primarily comprised of students who activity engaging in learning, may not be sensitive to the benefits of the N-IGMA. The N-IGMA may therefore be better suited for individuals with cognitive deficits and those who are not actively engaged in learning.

An additional delimitation was the length of the training intervention and the absence of a follow-up in the months following the post-training assessment. While the length was specifically chosen based on previous research (Clouter, 2013), it is possible a longer training period may have facilitated strong transfer of learning effects. As well, some previous research has used three month follow-up to determine if transfer of learning effects can be maintained over time without additional cognitive training (Jaeggi et al., 2011). Additional follow-up testing in weeks or months after the completion of training may help decipher between learning effects and test-retest effects.

The stimulus set changes used in the N-IGMA were to maintain participants' motivation and engagement to the task. However, the reset to N=1 with each new stimulus set may result in a decrease of motivation and it may hinder the success of the task. Some participants may have found certain stimulus sets to be more challenging than others and this may have resulted in a decrease of motivation and engagement. There was no direct measure taken to determine if participants enjoyed playing the N-IGMA or Blockmaster. The results of the current study demonstrated both groups completed approximately the same number of training sessions; however, we are unable to determine if both training tasks were equally enjoyed or if the groups simply demonstrated high compliance. Future research should consider a quantitative measure of enjoyment, to further understand the engagement and enjoyment of playing the N-IGMA.

Learning the structure of the N-IGMA task may have been a difficult path to learning for some participants compared to others and may have hindered their initial performance. As well, participants who found the task to be harder than others may not have been as motivated and engaged in the task while completing the at-home training sessions. Blockmaster, however, may not have been novel enough. Tetris is a well-known, casual game to play. The version of Blockmaster used did not have any changing stimuli, and may need to have changing stimuli colours to be more novel.

Using an active control group is a delimitation of the current study and highlights the absence of a passive no-contact control group. Had a passive no-contact control been used, data analysis could determine whether or not the results of the current study are due to test re-test effects. Active control groups theoretically replicate the concept of a placebo group in pharmaceutical research; control for adherence to the training schedule and computer use. Therefore, based on the current trends and recommendation in current research, a passive no-contact control group was not used in the current study.

There were several factors out of the control of the researchers as the participants completed the tasks at-home. This was a known delimitation of this study as we purposefully planned to have the training sessions completed at-home and online, instead of requiring participants to come into the laboratory every day. Recent research has suggested there may be a benefit to completing training in the laboratory, suggesting training completed at-home is not as effective for facilitating transfer of learning effects

(Lampit, Hallock, Valenzuela, 2014). The participants were told to complete the tasks in distraction-free environments and in one sitting if possible. If participants were in distracting environments while playing the N-IGMA they would have had difficult attending to all the cues and this would have hindered their performance.

There were several different researchers involved with the collection of the data that may have caused some researcher bias in the way how the assessments were administered and how the training was given. Before testing the assessors and trainers were trained on the their corresponding task, all completed at least three practice trials before assessing or training participants used for data collect. The assessors were required to read the assessment protocols directly to ensure participants all heard the same instructions. The trainers were given more freedom with the training protocols, and had written manuals to use as guidelines. There was a fair distribution of assessors and trainers between the N-IGMA and Blockmaster seen in Table 16, and reflects the availability of the researchers involved.

Conclusion

Analysis of the outcome measures revealed no clear benefit for the N-IGMA as compared to Blockmaster since both groups improved equally on several measures. The improvements could be due to simple test/retest effects, however, it is equally plausible that Blockmaster is more effective than expected, perhaps targeting a working memory system and certain components of fluid intelligence. Games such as Blockmaster have a certain level of strategy-building involved, and it may be feasible that the visuospatial system targeted to complete the strategy building may be enough to improve components of working memory and fluid intelligence alike.

While the results of this study did not find any clear evidence of transfer of learning, the quest to continue to discover why some N-back training protocols lead to positive transfer effects need to be continued. Further consideration needs to be given to the individual differences that help explain positive and negative transfer of learning in working memory training. There were some indications in the current study that pre-training fluid intelligence had an impact, noted by positive correlations in the N-IGMA group and not the Blockmaster group; these possible linkages need to be explored. The further evolution of transfer of learning, and our understanding of the n-back task, will aid in the successful pursuit of effective working memory training interventions.

Lastly, the results of the current study suggest that there is some overlap between the MoveSpan and the SymSpan, which we suggest is the visuospatial sketch pad. The working memory system for observed action needs to be further explored. Broadening the literature for this system and understanding better how we use the system to understand the environment around us, may lead to a bridge between cognitive training and the motor training research fields.

References

Aboitiz, F., Aboitiz, S., & Garcia, R.R. (2010). The phonological loop: A key innovation in human evolution. *Current Anthropology, 51*(1), S55-S65. doi:10.1086/650525

Anguera, J.A., et al. (2013). Video game training enhances cognitive control in older adults. *Nature, 501*, 97-104. doi: 10.1038/nature12486

Au, J., Sheehan, E., Tsai, N., Duncan, G.J., Buschkuehl, M., & Jaeggi, M. (2014). Improving fluid intelligence with training on working memory: a meta-analysis. *Psychonomic Bulletin& Review*. Advanced online publication. doi: 10.3758/s13423-014-0699-x

Baddeley, A. (2000). The episodic buffer: A new component of working memory. *Trends in cognitive sciences, 4*(11), 417-423.

Baddeley, A. (2003). Working memory: Looking back and looking forward. *Nature Reviews Neuroscience, 4*(10), 829-839. doi:10.1038/nrn1201

Baddeley, A. (2007). *Working memory, thought, and action*, New York: Oxford University Press

Baker, J., Cote, J., & Abernethy, B. (2003). Sport-specific practice and the development of expert decision-making in team ball sports. *Journal of Applied Sport Psychology, 15*(1), 15-25. doi:10.1080/10413200305400

Bailey, H. R., Dunlosky, J., Hertzog, C. (2014). Does strategy training reduce age-related deficits in working memory? *Psychology and Aging, 24*(1), 82-92. doi: 10.1037/a0014078

Cattell, R. B., (1971). Abilities: their structure, growth, and action. Oxford, England: Houghton Mifflin.

Cattell, R. B., & Cattell, A. K. S. (1973). Measuring intelligence with the culture fair tests. Institute for Personality and Ability Testing.

Clouter, A. (2013). *The effects of dual n-back training on the components of working memory and fluid intelligence: An individual differences approach.* Unpublished manuscript, Dalhousie University, Halifax, Canada.

Cowan, N. (2010). The magical mystery four: How is working memory capacity limited, an why? *Current Directions in Psychological Science, 19*(1), 51-57. doi:10.1177/0963721409359277

Conway, A., Cowan, N., Bunting, M.F., Therriault, D.J., & Minkoff, S. (2002). A latent variable analysis of working memory capacity, short-term memory capacity, processing speed, and general fluid intelligence. *Intelligence, 30*, 163-183. doi:10.1016/S0160-2896(01)00096-4

Dahlin, E., Nyberg, L., Backman, L., & Nelly, A.S. (2008). Plasticity of executive functioning in young and older adults: Immediate training gains, transfer and long-term maintenance. *Psychology and Aging, 23* (4), 720-730. doi:10.1037/a0014296

Dehn, M.J. (2008). Working memory and academic learning: Assessment and intervention. Hoboken, New Jersey: John Wiley & Sons, Inc.

Green, C.S., & Bavelier, D. (2003). Action video game modifies visual selective attention. *Letters to Nature, 423*, 534-537. doi:10.1038/nature01647

Green, C.S., & Bavelier, D. (2008). Exercising your brain: A review of human brain plasticity and training-induced learning. *Psychology and Aging, 23*(4), 692-701. doi:10.1037/a0014345

Jaeggi, S. M., Buschkuehl, M., Jonides, J., Perrig, W.J. (2008). Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of Sciences of the United States of America, 105*(19), 6829-6833. doi: 10.1073/pnas.0801268105

Jaeggi, S. M., Buschkuehl, M., Jonides, J., Shah, P. (2011). Short- And long-term benefits of cognitive training. *Proceedings of the National Academy of Sciences of the United States of America, 108*(25), 10081-10086. doi:10.1073/pnas.1103228108

Jaeggi, S.M., Buschkuehl, M., Perrig, W. J., Meier, B. (2010). The concurrent validity of the n-back task as a working memory measure. *Memory, 18*(4), 394-412. doi:10.1080/09658211003702171

Jaeggi, S.M., Schmid, C., Buschkuehl, M., & Perrig, W.J. (2009). Differential age effects in load-dependent memory processing. *Aging, Neuropsychology, and Cognition, 16*(1) 80-102. doi: 10.1080/13825580802233426

Jarrold. C., & Towse, J.N. (2006). Individual differences in working memory. *Neuroscience, 139*(1), 39-50. doi.org/10.1016/j.neuroscience.2005.07.002

Kane, M.J., Conway, A.R., Miura, T.K., Colflesh, G.J., (2007). Working memory, attentional control and the N-back task: A question of construct validity. *Journal of Experimental Psychology, 33*(3), 615-622. doi:10.1037/0278-7393.33.3.615

Kane, M. J., & Engle, R. W. (2003). Working-memory capacity and the control of attention: The contributions of goal neglect, response competition, and task set to Stroop interference. *Journal of Experimental Psychology: General, 132* (1), 47. doi:10.1037/0096-3445.132.1.47

Kane, M. J., Hambrick, D. Z., Tuholski, S. W., Wilhelm, O., Payne, T. W., & Engle, R. W. (2004). The generality of working memory capacity: A latent-variable approach to verbal and visuospatial memory span and reasoning. *Journal of Experimental Psychology: General, 133*(2), 189. doi:10.1037/0096-3445.133.2.189

Karbach, J., & Kray, J. (2009). How useful is executive control training? Age differences in near and far transfer of task-switching training. *Developmental Science, 12*(6), 978-990. doi: 10.1111/j.1467-7687.2009.00846.x

Klein, K., & Fiss, W.H. (1999). The reliability and stability of the Turner and Engle working memory task. *Behaviour Research Methods, Instruments, & Computers, 31*(3), 429-432

Klingberg, T. (2010). Training and plasticity of working memory. *Trends in cognitive sciences, 14*(7), 317-324. doi:10.1016/j.tics.2010.05.002

Klingberg, T., Forssberg, H., & Westerberg, H. (2002). Training of working memory in children with ADHD. *Journal of Clincial and Experimental Neuropsychology, 24*(6), 781-791.

Lampit, A., Hallock, H., & Valenzuela, M. (2014). Computerized Cognitive Training in Cognitively Healthy Older Adults: A Systematic Review and Meta-Analysis of Effect Modifiers. *PLoS Med*, *11*(11). doi:10.1371/journal.pmed.1001756

Larsen, J.D., Baddeley, A., & Andrade, J. (2000). Phonological similarity and the irrelevant speech effect: Implications for models of short-term verbal memory. *Memory, 8*(3), 145-157. doi:10.1080/096582100387579

Luciana, M., Depue, R.A., Arbisi, P., & Leon, A. (1992). Facilitation of working memory in humans by a D2 Dopamine receptor agonist. *Journal of Cognitive Neuroscience, 4*(1), 58-68. doi:10.1162/jocn.1992.4.1.58

Magill, R.A. (2007). *Motor learning and control: Concepts and applications.* New York: McGraw-Hill.

Miller, G.A. (1956). The magical number seven plus or minus two: some limits on our information processing. *Psychological Review, 63*, 81-97. doi:10.1037/0033-295X.101.2.343

Nouchi, R., et al. (2012). Brain training game improves executive functions and processing speed in the elderly: A randomized controlled trial. *Plos One, 7*(1). doi:10.1371/journal.pone. 0029676

Olesen, P.J., Westerberg, H., & Klingberg, T. (2004). Increased prefrontal and parietal activity after training working memory. *Nature Neuroscience, 7*(1), 75-79. doi:10.1038/nn1165

Owens, A.M., et al. (2010). Putting brain training to the test. *Nature, 465*(10), 775-778. doi:10.1038/nature09042

Park, D.C., & Reuter-Lorenz, P. (2009). The adaptive brain: Aging and neurocognitive scaffolding. *Annual Review of Psychology, 60,* 173-196. doi: 10.1146/annurev.psych.59.103006.093656

Passolungi, M.C & Mammarella, I. (2012). Selective spatial working memory impairment in a group of children with mathematics learning disabilities and poor problem-solving skills. *Journal of Learning Disabilities, 45*(40), 341-350. doi:10.1177/0022219411400746

Redick, T.S., et al. (2012). Measuring working memory capacity with automated complex span task. *European Journal of Psychological Assessment, 28*(3), 164-171. doi: 10.1027/1015-5759/a000123

Repovs, G., & Baddeley, A. (2006). The multi-component model of working memory: Explorations in experimental cognitive psychology. *Neuroscience, 139*(1), 5-21. doi.org/10.1016/j.neuroscience.2005.12.061

Roelfsema, P.R., van Ooyen, A., & Watanabe, T. (2010). Perceptual learning rules based on reinforcers and attention. *Trends in Cognitive Sciences, 14*(2), 64-71. doi: 10.1016/j.tics.2009.11.005

Shelton, J.T., Elliott, E.M., Hill, B.D., Calamia, M.R., Gouvier, W.D. (2009). A comparison of laboratory and clinical working memory tests and their prediction for fluid intelligence. *Intelligence, 37*(1), 283- 306. doi:10.1016/j.intell.2008.11.005

Shelton, J.T., Metzger, R.L., & Elliot, E.M. (2008). A group-administered lag task as a measure of working memory. *Behaviour Research Methods, 39*(3), 482-493. doi:10.3758/BF03193017

Smyth, M. M., & Pendleton, L. R. (1989). Working memory for movements. *The Quarterly Journal Of Experimental Psychology A: Human Experimental Psychology*, 41(2-A), 235-250.

Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, *18,* 643–662.

Turner, M. L., & Engle, R. W. (1989). Is working memory capacity task dependent? Journal of Memory & Language, *28*, 127-154.

Unsworth, N., & Engle, R. (2005). Working memory capacity and fluid abilities: Examining the correlation between Operation Span and Raven. *Intelligence, 33*, 67-81. doi:10.1016/j.intell.2004.08.003

Van der Elst, W., Van Boxtel, M. P., Van Breukelen, G. J., Jolles, J. (2006). The Stroop color-word test: Influence of age, sex, and education; and normative data for a large sample across the adult age range. *Assessment, 13*(1), 62-79. doi: 10.1177/1073191105283427

Westerburg, H., et al. (2007). Computerized working memory training after stroke – a pilot study. *Brain Injury, 21*(1), 21-29. doi:10.1080/02699050601148726

Wood, J,. N. (2007). Visual working memory for observed actions. *Journal of Experimental Psychology, 136*(4), 639-652.

Zacks, J. M., & Tversky, B. (2001). Event structure in perception and conception. *Psychological Bulletin*, *127,* 3–21.

Zimmer, H.D., Munzer, S., & Umla-Runge, K. (2010). Visuo-spatial working memory as a limited resource for cognitive processing. In M.W Crocker & J. Siekmann (Eds), *Resource-adaptive cognitive processes* (pp. 13-34). Berlin Heidelberg: Springer - Verlag. doi:10.1007/978-3-540-89408-7 2

Appendix A: Self-Reported Screening Form

Code:_________________ Date:___________________

Email address:	Gender:
Phone number:	Writing hand:
Date of birth:	Education (years in school):
Age:	First Language: Language in school:
	Occupation:

Medical Information

What is your general state of health? Excellent Very Good Good Fair Poor

Have you ever been diagnosed or treated for a head injury with loss of consciousness?

Do you have any other neurological problems (e.g., MS, Seizures, movement disorder)?

Do you have any psychiatric problems (e.g., a diagnosis of depression, anxiety disorder)?

Do you have any learning disabilities (e.g., attention deficit disorder or dyslexia)?

Medications

Computer Experience (within last six months):

How many hours per week do you use a computer?

What are the three computer programs that you use most often?

1.
2.
3.

Video Gaming Experience (within last six months):

How many hours per week do you play video games?

What are your top three games, and what is the highest level that you have reached in each game?

1.
2.
3.

Appendix B: Example of Recruitment Poster

How Do Computer Activities Affect Memory and Thinking?

What is the purpose of this study?

To investigate the effects of various computer activities on different memory and thinking skills.

What does the study include?

Participants will engage in computer activities at home for 3 weeks. Tests of memory and thinking will be given in our lab at the beginning and at the end of the 3 weeks.

Who can participate?

Healthy adults (19-30) who own a laptop with an external mouse and are fluent in English.

Is there compensation?

Compensation is provided at $10/hr up to a total of 12 hours, for a maximum of $120.00

Whom do I contact?

Jacob Kroeker @ thecatstudy@gmail.com or 1-902-494-4033

Computer Activities
thecatstudy@gmail.com

Computer Activities
thecatstudy@gmail.com

Computer Activities
thecatstudy@gmail.com

Computer Activities
thecatstudy@gmail.com

Computer Activities
thecatstudy@gmail.com

Computer Activities
thecatstudy@gmail.com

Computer Activities
thecatstudy@gmail.com

Computer Activities
thecatstudy@gmail.com

Computer Activities
thecatstudy@gmail.com

Computer Activities
thecatstudy@gmail.com

Appendix C: CFIT example.

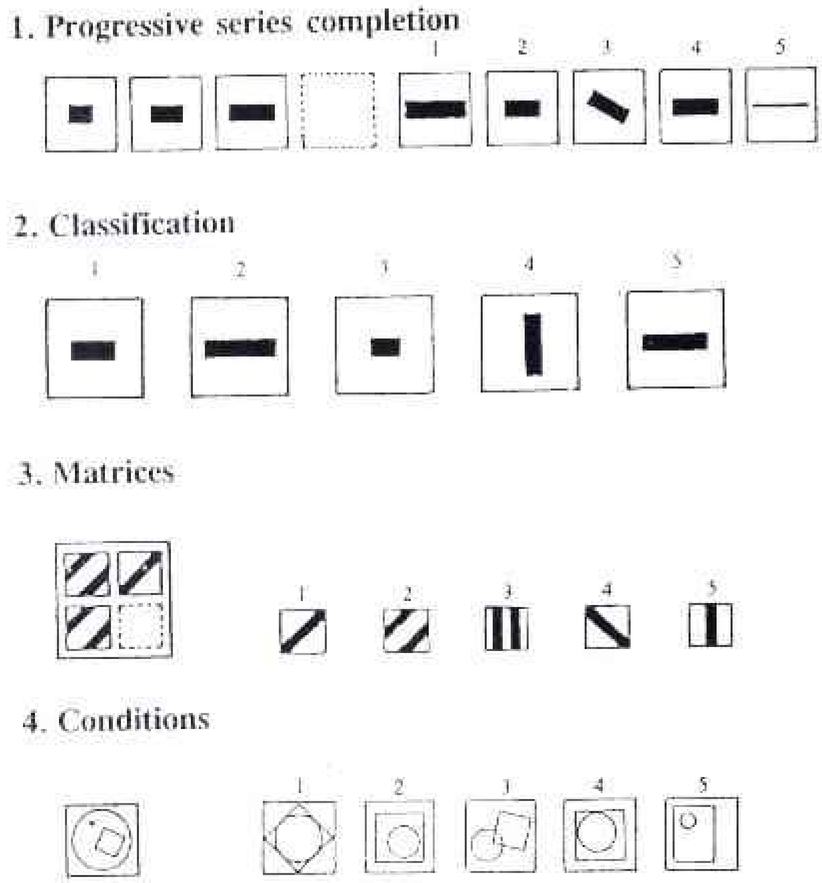

Figure 1. Depiction of the CFIT subtests.

Appendix D: The OSPAN task.

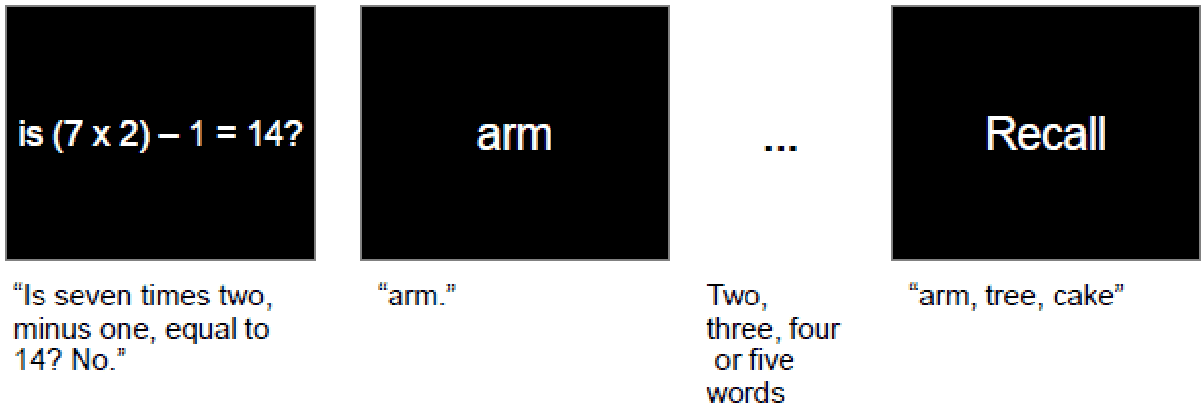

Figure 2. Depiction of the OSPAN (Clouter, 2013).

Appendix E: Example of the symmetry span task

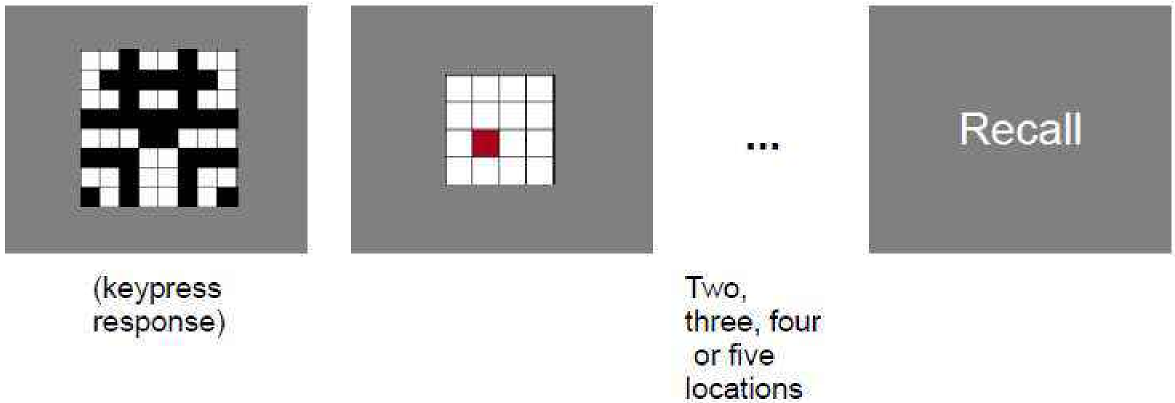

Figure 3. Depiction of the symmetry span task (Clouter, 2013).

Appendix F: The Stroop task

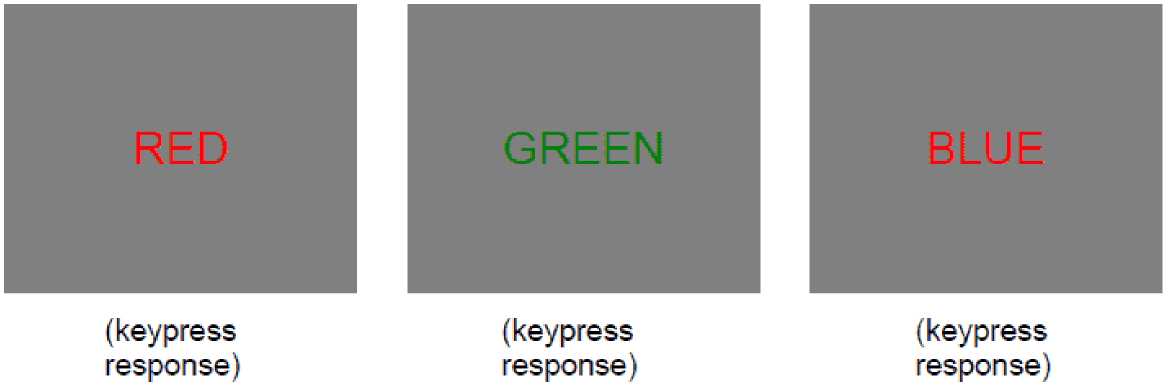

Figure 4. Depiction of the Stroop task (Clouter, 2013).

Appendix G: The MoveSpan task

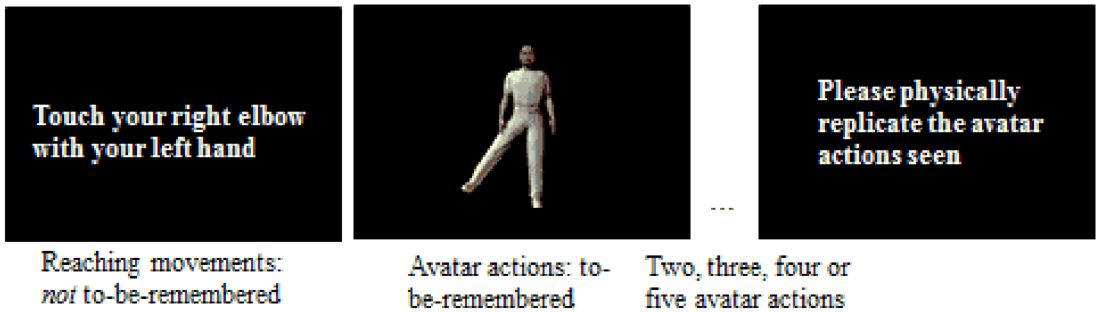

Figure 5. Depiction of the MoveSpan task (Wood, 2007).

Appendix H: Informed Consent

Department of Psychology
Halifax, Nova Scotia
Canada B3H 4J1
Tel: 902.494.3417
Fax: 902.494.6585
www.dal.ca/psychology

CONSENT FORM

Title of study: The Impact of Computer Based Activities on Thinking and Memory Tests

Introduction
We invite you to take part in a research study, supervised by Dr Raymond Klein (Principal Investigator) & Dr. Gail Eskes (Site Investigator). Your participation in this study is voluntary and you may withdraw from the study at any time. The study is described below. This description tells you about the risks, inconvenience, or discomfort which you might experience. Participating in the study might not benefit you, but we might learn things that will benefit others. You should discuss any questions you have about this informed consent with the person conducting it.

What is the purpose of this?
The purpose of this study is to investigate different computer activities and their influence on different neuropsychological tests.

What you will be asked to do?
You will be asked to answer general non-revealing demographic questions and questions about your gaming experience. Overall we will meet with you two times for 2.5 hours. During your first visit, you will be given a variety of thinking and memory tests for 2 hours. The investigator will then walk you through a tutorial session of your computer activity. Subsequent sessions will be performed from your own laptop using an external mouse for up to 30 minutes a day, 5 days a week, for three weeks. Your last session will be completed in the lab (3 weeks later) with the same tests as performed during your initial visit. The outcomes of this study will help us better understand the impacts of different computer activities on different types of thinking and memory tests.

Who can participate (Inclusion Criteria)?
1. Healthy (by self-report) adults (between 19-30 years of age).
2. Persons with normal or corrected-to-normal visual acuity.
3. Those who play less than one hour of video games per day (in an average week).
4. Persons with own laptop with external mouse.
5. Highly fluent in English.

Who cannot participate (Exclusion Criteria)?

1. Self-reported history of head injury with loss of consciousness
2. Self-reported history of any neurological or neurosurgical disorder i.e., stroke, epilepsy, Parkinson's disease, Huntington's disease, Multiple Sclerosis.
3. Self-report of treatment for severe psychiatric disorder that would interfere with testing (e.g., depression or anxiety).
4. Self-report of learning disabilities (e.g., attention deficit disorders or dyslexia).

Who will be conducting the research?

Dr. Raymond Klein Principal Investigator Dalhousie University ray.klein@dal.ca	Dr. Gail Eskes Co-investigator Dalhousie University gail.eskes@dal.ca	Dr. Joshua Salmon Researcher, Contact Person Dalhousie University joshua.salmon@dal.ca
Amy Heffernan, BSc Graduate Student Dalhousie University am568861@dal.ca	Kerry Clifton, BSc Research Coordinator Dalhousie University K.Clifton@dal.ca	Franziska Kintzel, MSc Research Assistant Dalhousie University fkintzel@dal.ca
Richard Patrick Research Assistant Dalhousie University rationalrichard@gmail.com	Amanda Glenn Research Assistant Dalhousie University am723007@dal.ca	Sarah Dolan, BScH Research Assistant Dalhousie University sarah.dolan@dal.ca
Jacob Kroeker Web-developer Dalhousie University jakekroeker@gmail.com	Dr. Stephanie Jones Post-doctoral Research Fellow Dalhousie University stephaniejones03@hotmail.com	

Phone: (902) 494-4033

Possible Risks and Discomforts
There is minimal possibility of risk and discomfort.

Possible Benefits
There may be no direct personal benefits for completing this survey. Indirectly however, we hope to gain new knowledge to contribute to the design of better research protocols.

Compensation
Financial compensation will be available to all participants at a prorated amount of $10/hour.

Students who participate in the study for credit will receive up to four bonus credit points towards their grade if they are in an eligible psychology class, following the Psychology department's REB-approved procedures, in addition to prorated compensation at

$10/hour for the rest of their time (for a maximum of 4 credit points + $ 80). Participants who either chose not to receive credit points, or are ineligible for points will receive prorated compensation for up to a maximum of 12 hours of time, or $120. Compensation will be prorated and reduced based on the number of completed sessions, meaning participants must complete all sessions to receive full compensation. If you are unable to complete a minimum of 10 training sessions before the final assessment you will be withdrawn from study and not permitted to complete the final assessment. The website/server will keep track of how many sessions you complete.

If you withdraw or are withdrawn by the researchers, at any point throughout the study, you will receive compensation for sessions you have completed to the point when you decided to withdraw or were withdrawn.

Confidentiality
Your data will be confidential and de-identified by labeling it with a maximum eight digit numeric code. You will not be identified in any reports or publications. You can indicate at the bottom whether you wish to have quotations used from you or not by checking the appropriate box.

Your data will be collected with paper and pencil and/or computer and stored in a controlled-access building, in locked filing cabinets in Dr. Eskes lab, or online in encrypted, password-protected folders hosted on a password-protected server at Dalhousie University. Data will be stored for a minimum of five years in a locked filing cabinet in Drs. Klein or Eskes' lab. Only Drs. Ray Klein, Gail Eskes, or qualified research personnel in their laboratories, will have access to your data. For contact information see page one of this consent form.

Questions
If you have any additional questions or concerns about this study, please feel free to contact us directly at 494-4033.

Ask for:
Dr. Joshua Salmon
Joshua.salmon@dal.ca

Problems or Concerns
In the event that you have any difficulties with, or wish to voice a concern about, any aspect of your participation in this study, you may contact member of the Human Research Ethics / Integrity Coordinator at Dalhousie University's Office of Human Research Ethics and Integrity for assistance. Phone: 494-3423, Email: ethics@dal.ca

Appendix I: Trainer Emails to Participants

Day 3

- ✓ Email participant to determine if they are having any problems.

Email:

Hi (participant's name)

It's (Your name) from the computer activity study you've signed up for. I would like to thank you again for signing up to participant in our study; your participation is very valuable to us.

How are you doing with your daily activity, have you encountered any problems, or have any questions or concerns?

Please remember to be tracking your results on your computer activity log, and to be minimizing distractions while completing your activity!

Thank you,

(Your name)

Day 6

- ✓ Email participant.
- ✓ Change config files to Congfig 2, week 2.

Email:

Hi (participant's name)

Thank you for completing week 1 of our study, you have now completed __ daily activities. (Add comments based on their performance, e.g. you have completed all of them, great work! Or you've completed 4, great work! As a reminder in the next week you are able to complete 6 sessions to keep yourself on track to complete all 15 activities.)

Do you have any questions or concerns?

I would like to remind you that tomorrow the clues that you hear and see will change. Tomorrow you will see a lighthouse. Each clue presented will be a picture of the same lighthouse, however the position of the lighthouse will change; therefore, you are looking for back-to-back matches where the lighthouse is in the same position. The auditory clues will change to numbers instead of letters, but the goal is still the same: you are listening for back-to-back matches of the number clues. When the activity begins, you will start at level 1; this is a function of the program.

Are you finding it challenging to minimizing distractions while you are completing your activity?

Thank you,

(Your name)

Day 13

- ✓ Email participant.
- ✓ Change config files to CogFig 3, week 3.

Email:

Hi (participant's name)

Thank you for completing week 2 of our study, you have now completed __ daily activities. (Add comments based on their performance, e.g. you have completed all of them, great work! Or you've completed 4, great work! As a reminder in the next week you are able to complete 6 sessions to keep yourself on track to complete all 15 activities.) You're almost done!

How have you been finding doing the daily activity? Have you been able to successfully minimizing distractions while you are completing your activity?

I would like to remind you that tomorrow the clues that you hear and see with change. Tomorrow you will see different landscapes. The goal is the still the same, you are looking for back-to-back matches of the same landscape image. The auditory clues will change to words from the phonetic alphabet such as alpha and bravo, but the goal is still the same: you are listening for back-to-back matches. When the activity begins you will start at level 1; this is a function of the program.

Also, just a reminder that your final assessment is scheduled for ___, if you have any problems or need to reschedule please contact me as soon as you can.

Please remember to be tracking your results on your computer activity log!

Thank you,

(Your name)

Day 19

- ✓ Email participant

Hi (Participant name)

Congratulations you have completed phase 2 (if done all activities!) Now all you have to do is come back into the lab for your final assessment _____.

Or congratulations you have almost completed phase 2, you have 2 days to complete your activities, then you will have completed phase 2, then all you need to do is return to the lab.

Please remember to bring in your computer activity log.

The assessment will be at the same location as your first assessment in the Life Science Research Institute (which is attached to the Tupper building) at 1348 Summer Street, on the second floor.

If you have any problems or need to reschedule please contact me as soon as you can.

Thank you,

(Your name)

Trainer's Manual for Blockmaster Users

Day 3

- ✓ Email participant to determine if they are having any problems.

Email:

Hi (participant's name)

It's (Your name) from the computer activity study you've signed up for. I would like to thank you again for signing up to participant in our study; your participation is very valuable to us.

How are you doing with your daily activity, have you encountered any problems, or have any questions or concerns?

Please remember to be tracking your results on your computer activity log and to be minimizing distractions while completing your activity!

Thank you,

(Your name)

Day 6

- ✓ Email participant

Email:

Hi (participant’s name)

Thank you for completing week 1 of our study, you have now completed __ daily activities. (Add comments based on their performance, e.g. you have completed all of them, great work! Or you’ve completed 4, great work! As a reminder in the next week you are able to complete 6 sessions to keep yourself on track to complete all 15 activities.)

Do you have any questions or concerns?

Are you finding it challenging to minimizing distractions while you are completing your activity?

Thank you,

(Your name)

Day 13

- ✓ Email participant.

Email:

Hi (participant’s name)

Thank you for completing week 2 of our study, you have now completed __ daily activities. (Add comments based on their performance, e.g. you have completed all of them, great work! Or you’ve completed 4, great work! As a reminder in the next week you are able to complete 6 sessions to keep yourself on track to complete all 15 activities.) You’re almost done!

How have you been finding doing the daily activity? Have you been able to successfully minimizing distractions while you are completing your activity?

Also, just a reminder that your final assessment is scheduled for ___, if you have any problems or need to reschedule please contact me as soon as you can.

Please remember to be tracking your results on your computer activity log!

Thank you,

(Your name)

Day 19

- ✓ Email participant

Hi (Participant name)

Congratulations you have completed phase 2 (if done all activities!) Now all you have to do is come back into the lab for your final assessment _____.

Or congratulations you have almost completed phase 2, you have 2 days to complete your activities, then you will have completed phase 2, then all you need to do is return to the lab.

Please remember to bring in your computer activity log.

The assessment will be at the same location in the Life Science Research Institute at 1348 Summer Street, on the second floor.

If you have any problems or need to reschedule please contact me as soon as you can.

Thank you,

(Your name)

Appendix J: Count of Self-Reported Video Games Played

Self-Reported Video Games Played		
	N-IGMA	Blockmaster
Call of Duty	1	0
Candy Crush	4	1
Diablo	0	1
Donkey Kong	1	1
Jetpack joyride	1	0
League of Legends	0	1
Mario Cart	1	0
Minion rush	0	1
Sims 3	1	0
Skyrim	1	0
Solitaire	1	0
Super Mario Party	0	1
Super smash Bros	0	1
Tetris	1	2

Appendix K: Tables

Table 1

Descriptive statistics, Within Subject (Pre- and Post-Training) and Between Subjects (Group) Interactions for Each Outcome Measure

	Pre-training Mean (SD) N-IGMA	Post-training Mean (SD) N-IGMA	Pre-training Mean (SD) Blockmaster	Post-training Mean (SD) Blockmaster	Time Main Effect (Within Subject) (F-STATISTIC)	Time Main Effect (Within Subjects) (P-VALUE)	Interaction effect (Within Subject) (F-STATISTIC)	Interaction effect (Within Subjects) (P-VALUE)	Group Main Effect (Between Subjects) (F-STATISTIC)	Group Main Effect (Between Subject) (P-VALUE)
CFIT Test 1	7.44(1.33)	7.89(1.36)	7.40 (1.65)	8.00 (1.5)	1.24	0.280	0.028	0.870	0.005	0.946
CFIT Test 2	5.89(1.27)	9.22(1.72)	6.20(1.75)	8.30(1.16)	64.42*	<.001*	3.319	0.086	0.261	0.616
CFIT Test 3	7.22(1.40)	6.78(1.56)	6.90(1.20)	7.10(.88)	0.151	0.702	1.051	0.320	0.000	1.000
CFIT Test 4	6.89(.93)	8.90(1.05)	5.80(1.23)	7.60(1.08)	36.80*	<.001*	0.102	0.753	9.50+	0.007+
CFIT Overall	27.474(3.40)	32.78(2.91)	26.30(2.91)	31.0(3.06)	79.40*	<.001*	0.316	0.581	1.280	0.274
OSPAN SS 2	5.89(.33)	5.78(.44)	5.70(.48)	5.60 (.70)	0.304	0.588	0.001	0.977	0.001	0.977
OSPAN SS 3	7.00(1.80)	8.00(1.50)	7.40(1.58)	8.10(.99)	5.05+	0.038+	0.157	0.697	0.193	0.666
OSPAN SS 4	7.33(2.12)	9.00(3.04)	8.50(2.68)	9.80(1.55)	7.70+	0.013+	0.118	0.736	1.038	0.323
OSPAN SS 5	6.78(3.67)	7.67(2.60)	8.20(2.30)	8.40(1.78)	0.755	0.397	0.302	0.590	1.073	0.315
OSPAN Overall	27.00(5.45)	30.44(6.58)	29.80(4.87)	31.90(3.38)	8.331+	0.01+	0.490	0.493	0.969	0.339
SymSP SS 2	5.78(.44)	5.56(1.33)	5.40(.84)	5.50(.71)	0.065	0.802	0.453	0.510	0.433	0.519
SymSP SS 3	6.11(2.47)	6.56(2.51)	7.70(1.70)	7.50(1.90)	0.11	0.744	0.736	0.395	1.903	0.186
SymSP SS 4	8.56(3.18)	8.44(3.32)	7.70(2.98)	9.30(3.06)	2.143	0.161	2.831	0.111	0.000	1.000
SymSP SS 5	6.33(2.70)	7.89(4.29)	8.40(3.84)	8.80(3.91)	2.687	0.120	0.938	0.346	0.855	0.368
SymSP Overall	26.78(7.17)	28.44(9.96)	29.20(7.70)	31.10(7.68)	3.316	0.086	0.024	0.878	0.491	0.493
MoveSP SS 2	5.89(.33)	5.67(.48)	5.80(.42)	5.50(.71)	2.869	0.109	0.064	0.804	0.509	0.485
MoveSP SS 3	7.22(1.48)	7.78(2.22)	8.00(1.56)	6.90(1.91)	0.345	0.564	3.193	0.092	0.005	0.943
MoveSP SS 4	8.33(2.82)	7.22(2.81)	7.50(2.37)	6.70(1.70)	4.56+	0.048+	0.121	0.732	0.430	0.521
MoveSP SS 5	5.44(2.83)	6.78(3.07)	7.20(2.04)	6.80(2.57)	0.466	0.504	1.609	0.222	0.787	0.388
MoveSP Overall	26.89(6.25)	27.44(7.45)	28.50(4.20)	25.90(4.89)	0.898	0.356	2.140	0.162	0.000	0.989
RT Interference Cong.	.61(.08)	.61(.11)	.57(.09)	.56(.09)	0.169	0.686	0.013	0.910	1.016	0.328
RT Interference Incong	.78(0.17)	.76(.15)	.73(.12)	.71(.14)	0.465	0.504	0.016	0.901	0.695	0.416
RT Interfernce Stroop	.17(.10)	.15(.06)	.16(.10)	.15(.10)	0.55	0.469	0.077	0.785	0.049	0.827
Error Interference Cong	1.69(2.24)	2.45(1.82)	1.93(2.10)	2.41(3.25)	1.331	0.265	0.069	0.796	0.011	0.918
Error Interference Incong	4.012(3.70)	6.48(5.73)	8.89(9.52)	3.06(2.76)	0.787	0.387	4.803+	.043+	0.125	0.728
Error Interference Stroop	2.33(3.72)	4.03(6.00)	6.96(9.01)	.64(4.58)	1.344	0.26	4.06	0.06	0.09	0.77

Note. RT= response times. Cong = Congruent. Incong = Incongruent. Significant values of p<=.004 are noted with '*'. P-values between .05 and .004 considered trends are noted with '+'.

Table 2

Pearson Product Moment Correlations and Associated p-values for the Training Performance for Each Participant in the N-IGMA Group to the Change Scores for Each Outcome Measure.

		Pre-Assessment CFIT Score	Change CFIT	Change OSPAN	Change SymSpan	Change MoveSpan	Change in RT Cong	Change in RT Incong	Change RT Interference	Change in Errors Cong	Change in Errors Incong	Change Error Interference	Y-Intercept N-IGMA
Slope of average daily score of the N-IGMA	*PCC*	0.124	-0.437	-0.057	0.537	0.073	.158	.313	0.384	-.160	-.267	-0.202	-0.492
	P-Value (2-tailed)	0.751	0.239	0.884	0.136	0.852	.685	.412	0.308	.680	.487	0.602	.179

Note. RT= response times. Cong = Congruent. Incong = Incongruent. Change scores were calculated by post-training scores minus the pre-training scores.

Table 3

Pearson Product Moment Correlations and Associated p-values for the Training Performance for Each Participant in the Blockmaster Group to the Change Scores for Each Outcome Measure.

		Pre-Assessment CFIT Score	Change CFIT	Change OSPAN	Change SymSpan	Change MoveSpan	Change in RT Cong	Change in RT Incong	Change RT Interference	Change in Errors Cong	Change in Errors Incong	Change Error Interference	Y-Intercept Blockmaster
Slope of average daily score of Blockmaster	*PCC*	0.006	0.505	0.492	-0.213	0.151	.107	.263	0.302	0.072	0.304	0.156	-0.456
	P-Value (2-tailed)	.988	.136	.149	.556	.677	0.769	0.463	.396	0.844	0.393	.667	0.186

Note. RT= response times. Cong = Congruent. Incong = Incongruent. Change scores were calculated by post-training scores minus the pre-training scores.

Table 4

Pearson Product Moment Correlations and Associated p-values for the Correlations Performed Between the Starting N-level for the N-IGMA Group Compared to the Change Score Calculated for each Outcome Measure.

		Pre-Assessment CFIT Score	Change CFIT	Change OSPAN	Change SymSpan	Change MoveSpan	Change in RT Cong	Change in RT Incong	Change RT Interference	Change in Errors Cong	Change in Errors Incong	Change Error Interference
Y-Intercept of N-IGMA	*PCC*	.093	.341	.091	-.034	.294	.045	.174	.251	-.495	-.008	.143
	P-Value (2-Tailed)	*0.811*	0.37	0.816	0.931	0.443	.908	.655	0.515	.176	.984	0.714

Note. RT= response times. Cong = Congruent. Incong = Incongruent. Change scores were calculated by post-training scores minus the pre-training scores.

Table 5

Pearson Product Moment Correlations and Associated p-values for the Correlations Performed Between the Starting Levels for the Blockmaster Group Compared to the Change Score Calculated for each Outcome Measure.

		Pre-Assessment CFIT Score	Change CFIT	Change OSPAN	Change SymSpan	Change MoveSpan	Change in RT Cong	Change in RT Incong	Change RT Interference	Change in Errors Cong	Change in Errors Incong	Change Error Interference
Y-Intercept for Blockmaster	*PCC*	.357	-.531	-.354	0.833+	0.703+	-.105	-.129	-.123	0.251	-0.291	.184
	P-Value (2-Tailed)	.311	.114	.316	0.003+	0.023+	0.772	0.722	.735	0.484	0.414	.610

Note. RT= response times. Cong = Congruent. Incong = Incongruent. Change scores were calculated by post-training scores minus the pre-training scores. Significant values of $p<=.002$ are noted with '*'. P-values between .05 and .002 considered trends are noted with '+'.

Table 6

Descriptive Statistics for the Training Performance and Outcome Measures for the N-IGMA and Blockmaster Groups.

	N-IGMA		**Blockmaster**	
	Mean	**SD**	**Mean**	**SD**
Overall pre-training CFIT score	27.44	3.40	26.30	2.91
Change CFIT score	5.33	2.69	4.70	2.21
Change OSPAN score	3.44	3.00	2.10	5.00
Change SymSpan score	1.67	4.64	1.90	3.90
Change MoveSpan score	0.56	3.54	-2.60	5.52
Change response time congruent trials	0.00	0.07	-0.01	0.03
Change response time incongruent trials	-0.02	0.12	-0.01	0.09
Response time interference effect	-0.02	0.07	-0.01	0.07
Change in errors for congruent trials	0.77	2.22	-6.32	9.70
Change in errors for incongruent trials	2.47	6.87	0.48	2.48
Error interference effect	1.70	7.31	-5.83	9.30
Average daily N-level achieved (slope)	0.11	0.09	133.55	107.67
Starting level (y-intercept)	3.17	0.82	1963.89	1511.45

Table 7

Pearson Product Moment Correlations and p-values for the Correlations Between the Pre-training (pre-assessment) CFIT Score and Change Scores for all Outcome Measure for the N-IGMA Group.

		Change CFIT	Change OSPAN	Change SymSpan	Change MoveSpan	Change in RT Cong	Change in RT Incongruent	Change RT Interference	Change in Errors Cong	Change in Errors Incong	Change Error Interference	Slope of the N-IGMA	Y-Intercept N-IGMA
Pre-Assessment CFIT Score (N-IGMA)	*PCC*	-.565	0.848+	.416	.206	0.629	0.785+	0.749+	-0.485	.245	.377	.124	.093
	P-Value (2-tailed)	.113	0.004+	.266	.595	0.07	0.012+	0.02+	0.185	.525	.316	.751	.811

Note. RT= response times. Cong = Congruent. Incong = Incongruent. Significant values of p<=.002 are noted with '*'. P-values between .05 and .002 considered trends are noted with '+'.

Table 8

Pearson Product Moment Correlations and p-values for the Correlations between the Pre-training (pre-assessment) CFIT Score and Change Scores for all Outcome Measure for the Blockmaster Group.

		Change CFIT	Change OSPAN	Change SymSpan	Change MoveSpan	Change in RT Cong	Change in RT Incongruent	Change RT Interference	Change in Errors Cong	Change in Errors Incong	Change Error Interference	Slope of the N-IGMA	Y-Intercept N-IGMA
Pre-Assessment CFIT Score Blockmaster	*PCC*	-.312	-.056	.414	.365	0.34	-0.039	-0.217	-.118	.243	.263	.006	.357
	P-Value (2-tailed)	.379	.878	.234	.299	0.336	.914	.548	.745	.499	.462	.988	.311

Note. RT= response times. Cong = Congruent. Incong = Incongruent.

Table 9

Pearson Product Moment Correlations and p-values for the Correlations between the Overall Pre-training Scores for the OSPAN, SymSpan and the MoveSpan tasks.

		Overall pre-training OSPAN score	**Overall pre-training SymSpan score**	**Overall pre-training MoveSpan score**
Overall pre-training OSPAN score	PCC	-	0.423	0.256
	P-Value (2-tailed)	-	0.071	0.291
Overall Pre-training SymSpan score	PCC	0.423	-	.468+
	P-Value (2-tailed)	0.071	-	0.043+
Overall pre-training MoveSpan score	PCC	0.256	.468+	-
	P-Value (2-tailed)	0.291	0.043+	-

Note: Values considered trends between p-values of .05-.01 are marked with '+'.

Table 10

Pearson Product Moment Correlations and p-values for the Correlations between Overall Change Scores for the OSPAN, SymSpan, and MoveSpan tasks.

		Overall OSPAN change score	**Overall SymSpan change score**	**Overall MoveSpan change score**
Overall OSPAN change score	PCC	-	.084	.116
	P-Value (2-tailed)	-	.731	.638
Overall SymSpan change score	PCC	.084	-	.234
	P-Value (2-tailed)	.731	-	.334
Overall MoveSpan change score	PCC	.116	.234	-
	P-Value (2-tailed)	.638	.334	-

Table 11

Pearson Product Moment Correlations and p-values for the Correlations between the Overall Post-training Scores for the OSPAN, SymSpan, and the MoveSpan tasks.

		Overall post-training OSPAN score	**Overall post - training SymSpan score**	**Overall post - training MoveSpan score**
Overall post - training OSPAN score	PCC	-	.581*	.695*
	P-Value (2-tailed)	-	.009*	.001*
Overall post - training SymSpan score	PCC	.581*	-	.675*
	P-Value (2-tailed)	.009*	-	.002*
Overall post - training MoveSpan score	PCC	.695*	.675*	-
	P-Value (2-tailed)	.001*	.002	-

Note: Significant results of p<=.01 are have an asterisk's '*'.

Table 12

Counts for the Number of Time an Assessor and a Trainer Completed their Corresponding Tasks for each the N-IGMA and Blockmaster Groups.

		Blockmaster	N-IGMA	Guessed correctly
Assessors	Assessor 1	5	6	45%
	Assessor 2	2	2	25%
	Assessor 3	3	0	0%
	Assessor 4	0	1	0%
Trainers	Trainer 1	2	2	
	Trainer 2	5	5	
	Trainer 3	3	2	

Note: After the post-training assessment was completed, each assessor was asked to guess which group the participant had been assigned to. This was used as a measure to ensure assessors maintain blinded to the group the participant was assigned. The percent of correct guesses are listed in the table.

Appendix L: Figures

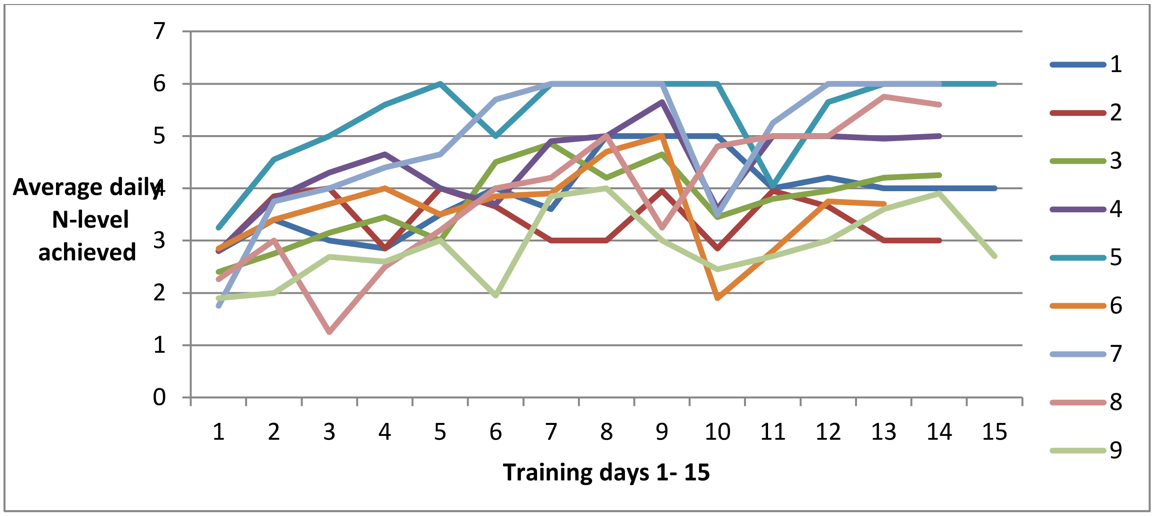

Figure 1. The average daily N-level achieved per participant. Day one is the first at-home training session. Six is the highest N-level possible in the N-IGMA.

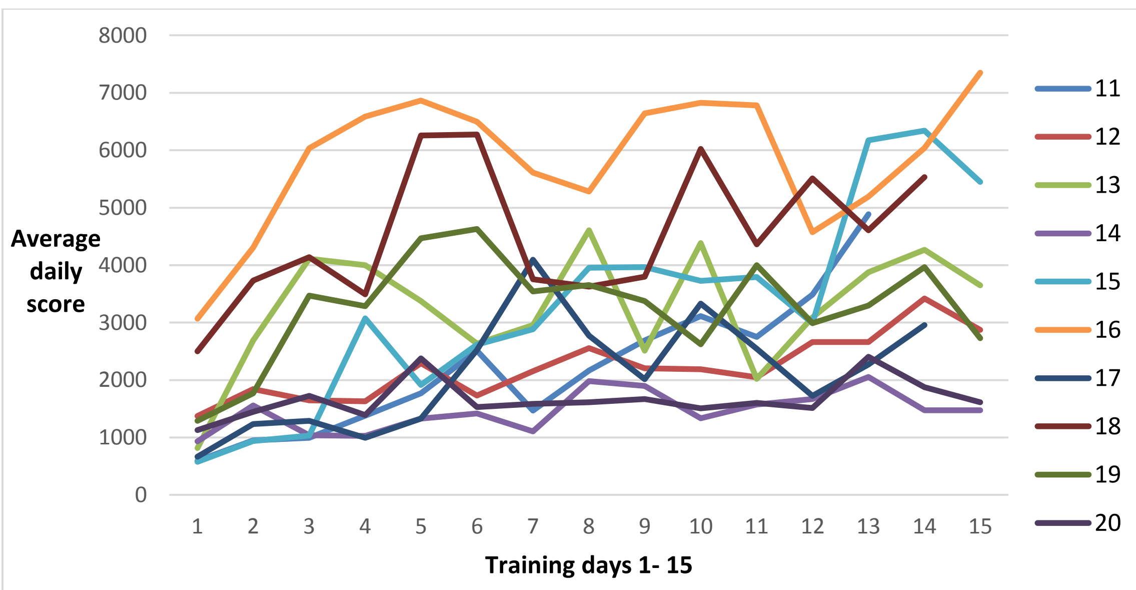

Figure 2. Average daily score achieved per participant in the Blockmaster group over the 15 at training sessions.

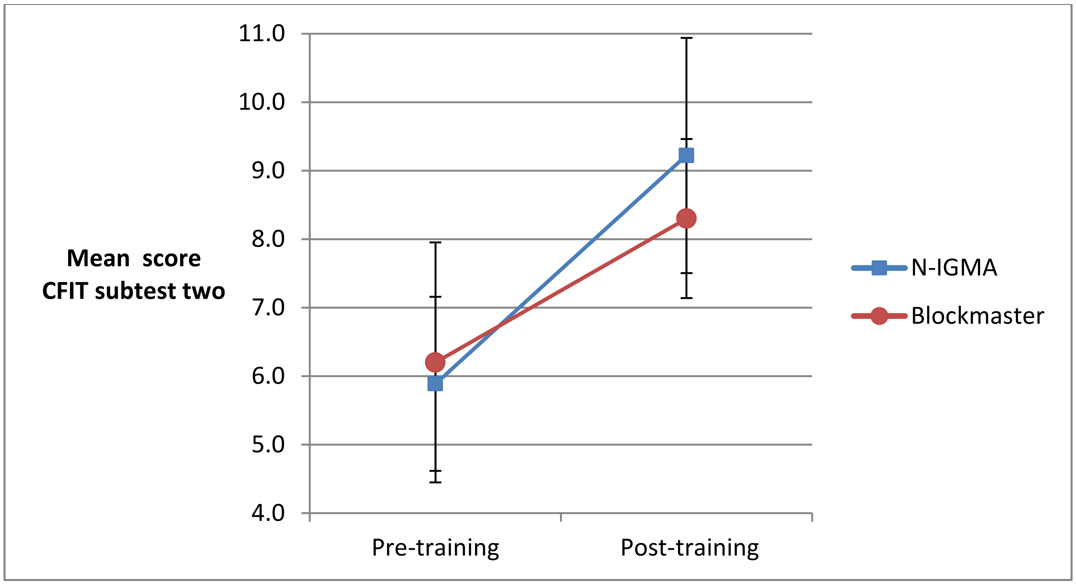

Figure 3. Mean scores for the CFIT "classification" subtest (test two) measured at pre-training and post-training, between the N-IGMA and Blockmaster groups. The results showed a significant time main effect, while the interaction effect did not reach significance.

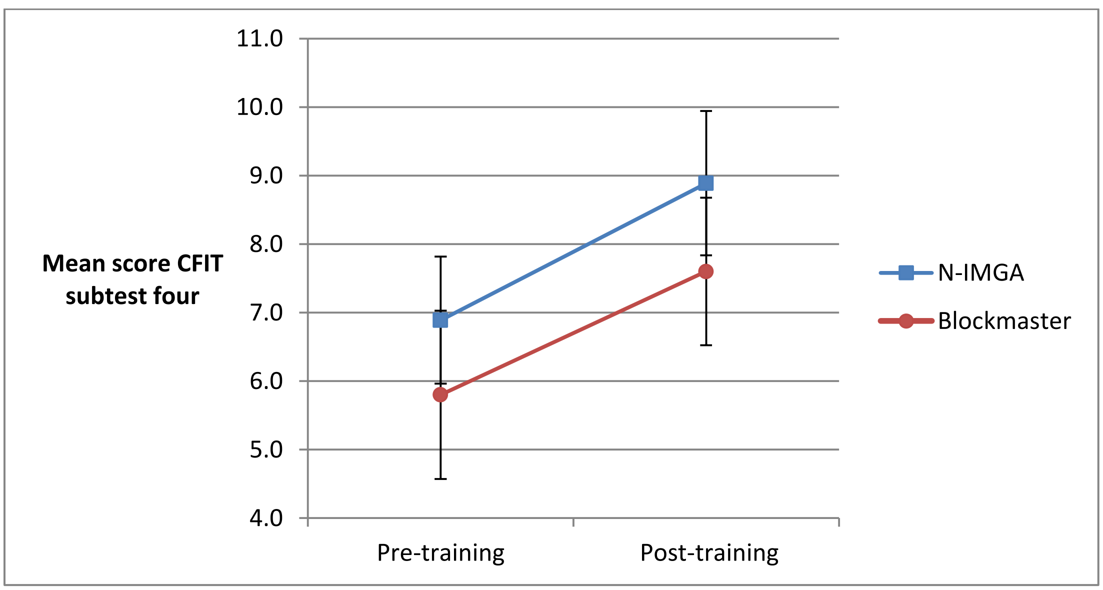

Figure 4. Comparing the mean score of CFIT "conditions" subtest (test four), measured at pre-training and post-training for both N-IGMA and Blockmaster groups. The results showed a significant time main effect.

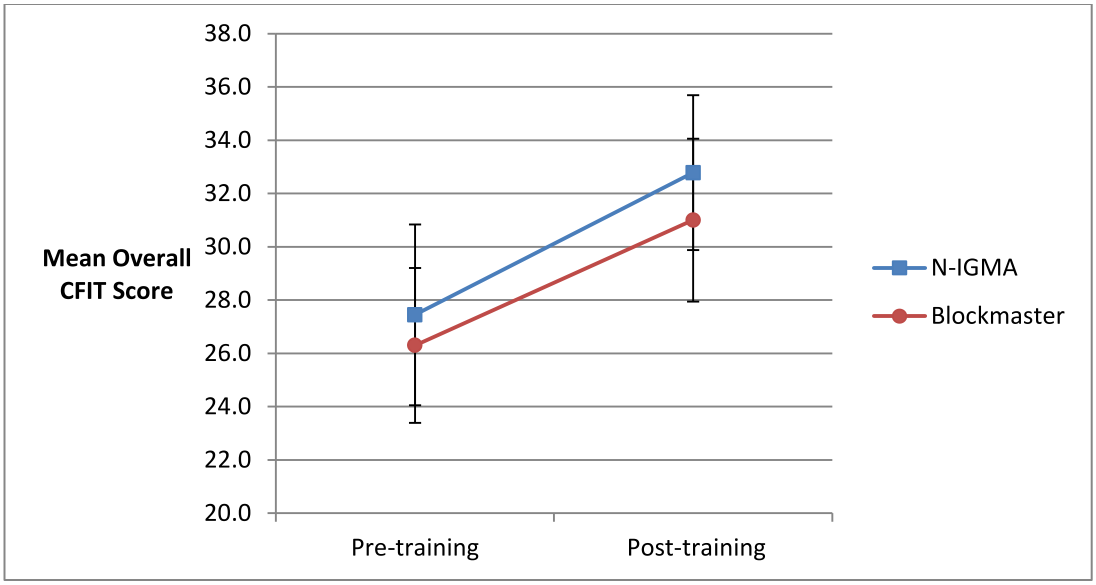

Figure 5. Comparing the mean of CFIT overall score (sum of subtests 1-4) measured at pre-training and post-training for both the N-IGMA and Blockmaster groups. The results showed a significant time main effect.

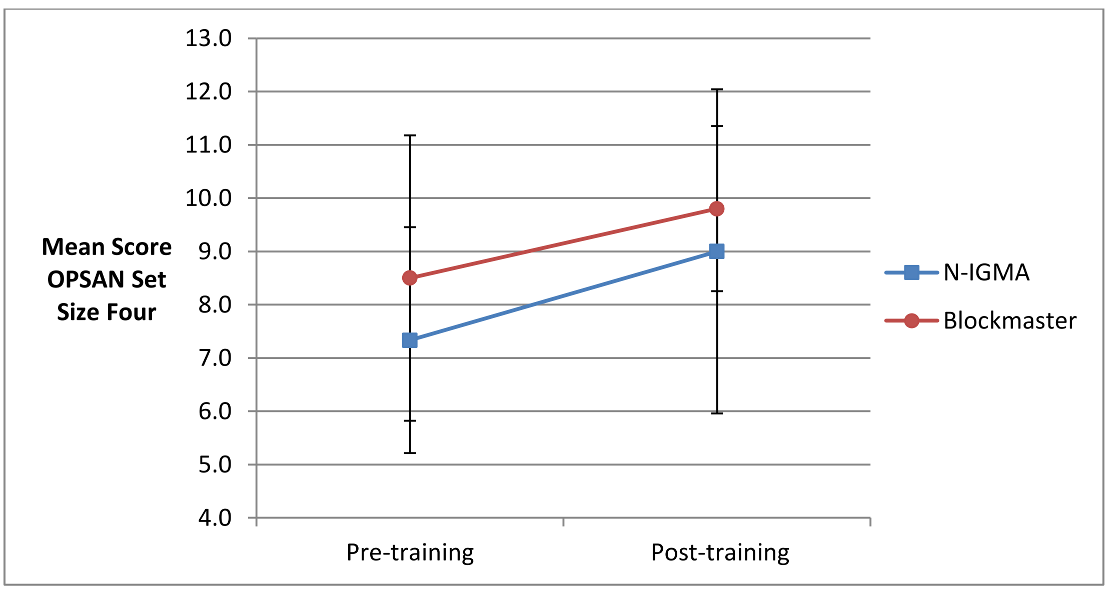

Figure 6. The mean number of words recalled for OSPAN set size 4 between pre- and post-training for both the N-IGMA and Blockmaster groups. Set size 4 requires participants to recall 4 words. The results showed a meaningful trend for the time main effect.

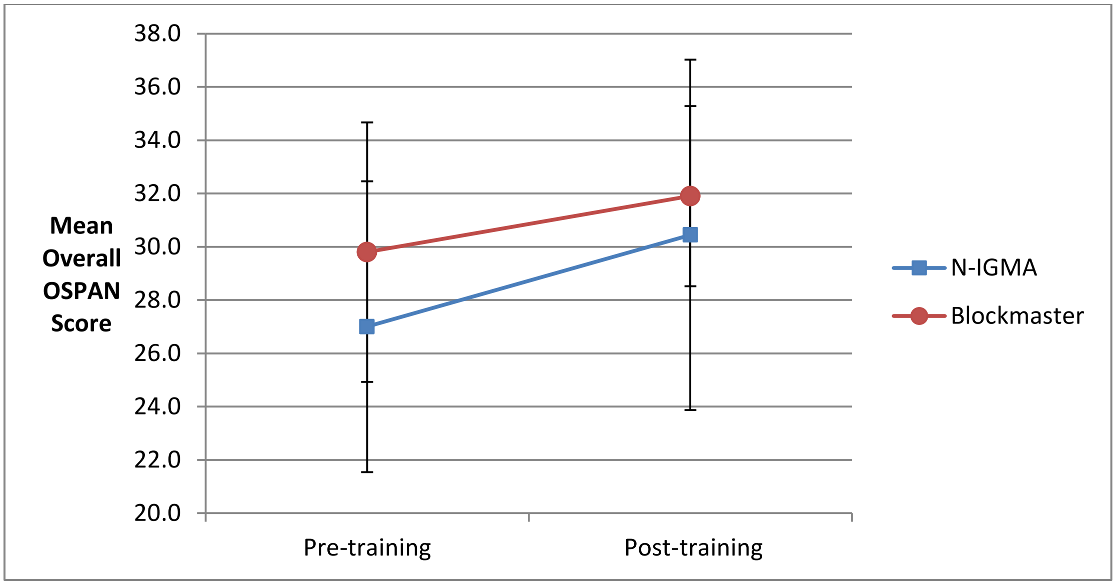

Figure 7. The overall mean number of words recalled during the OSPAN between pre- and post-training for both the N-IGMA and Blockmaster groups. The overall score includes set size 2 – 5. The results showed a meaningful trend for the time main effect.

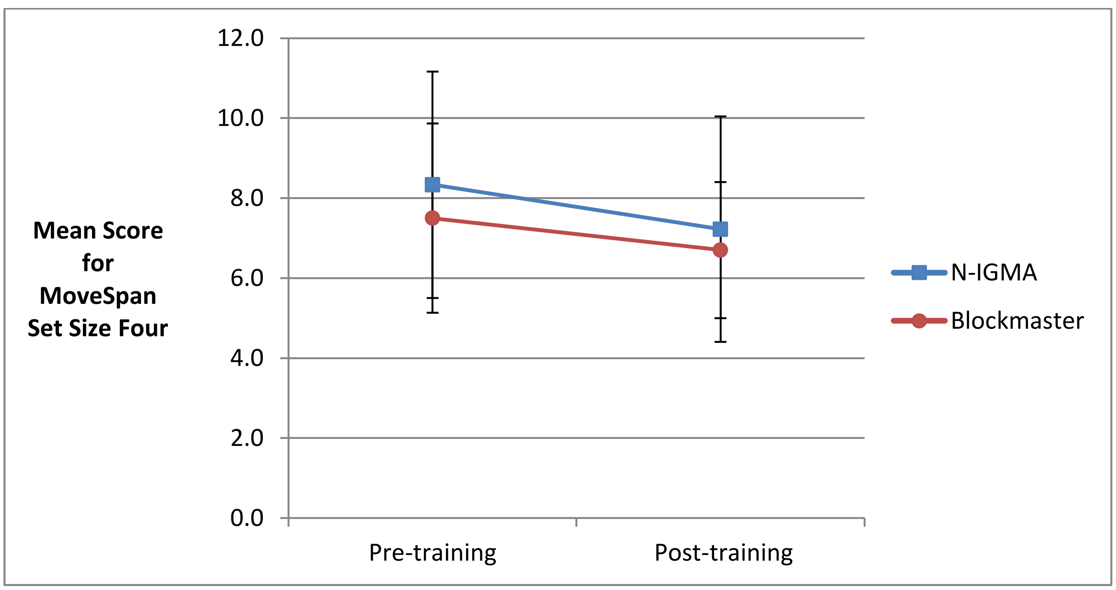

Figure 8. The mean number of observed actions recalled for set size 4 in the MoveSpan by both the N-IGMA and Blockmaster groups. The results showed a meaningful trend for the time main effect, and both groups decreased performance during the post-training assessement

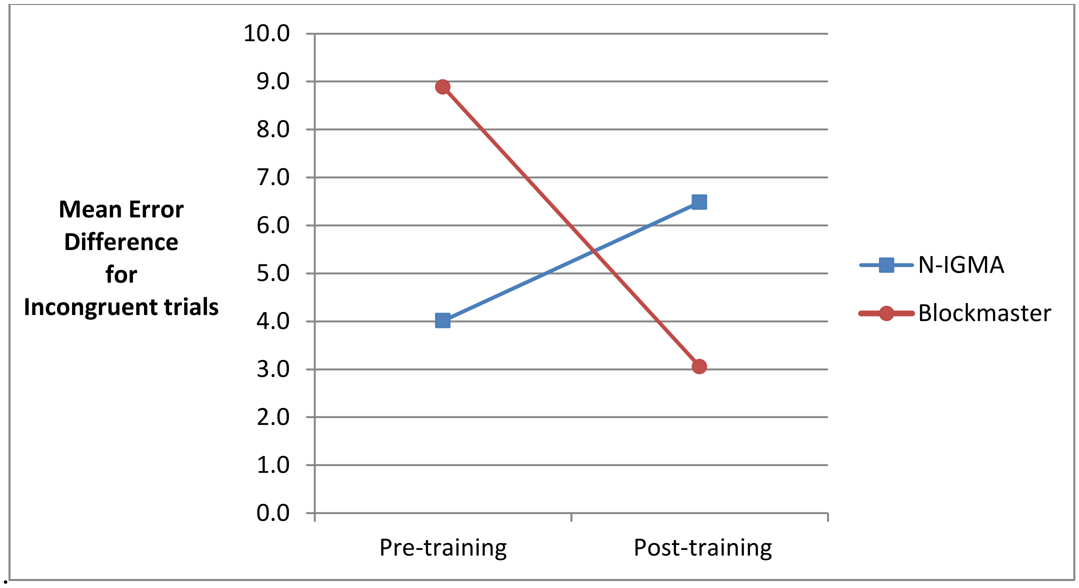

Figure 9. The Stroop task error differences for incongruent trials between pre-training and post-training assessments for both the N-IGMA and Blockmaster groups. The results showed a meaningful trend towards an interaction effect.

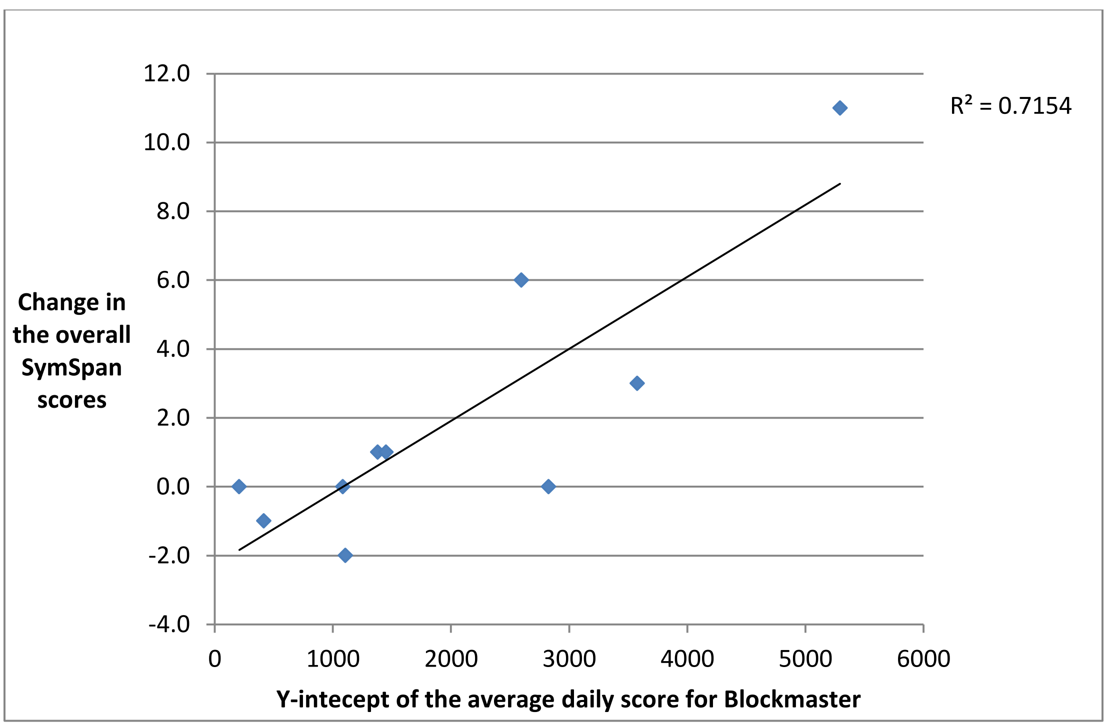

Figure 10. The line of best fit between the y-intercept of the average daily score for Blockmaster compared to the change in the overall SymSpan scores.

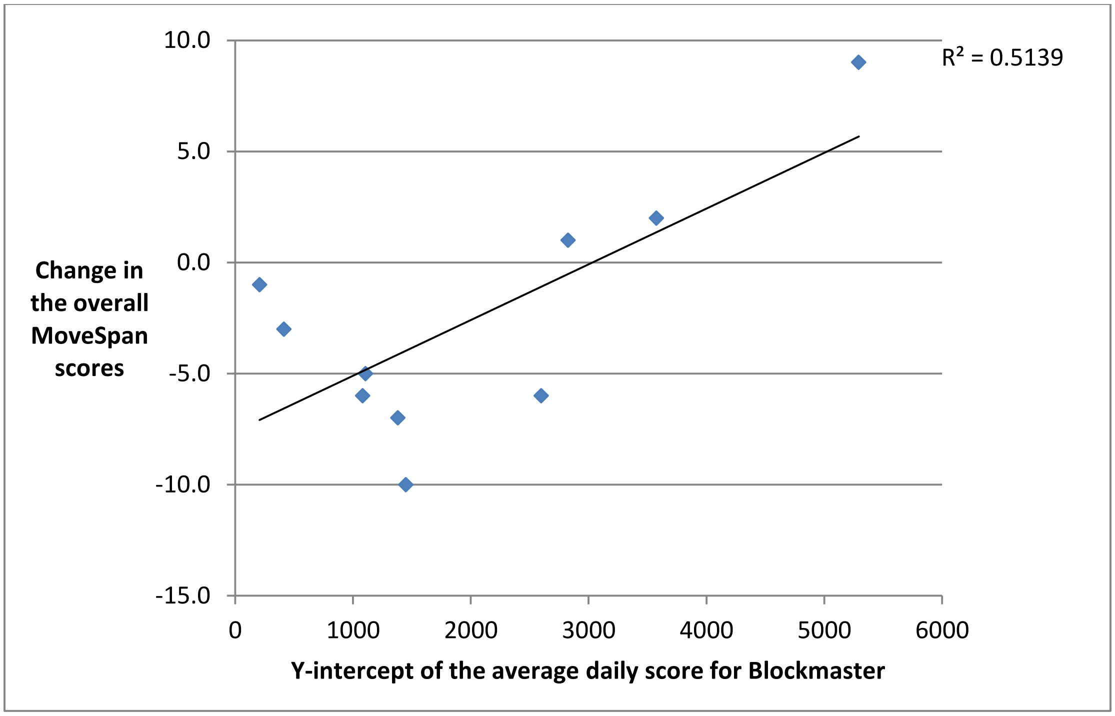

Figure 11. The line of best fit between the y-intercept of the average daily score for Blockmaster compared to the change in the overall MoveSpan scores.