

**INDIVIDUAL DIFFERENCES IN PROSPECTIVE MEMORY
PERFORMANCE:
A MICRO AND MACRO-ANALYTIC INVESTIGATION OF INTENTION
EXECUTION AND ONGOING TASK COST**

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Presented to
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Individual Differences in Prospective Memory Performance:
A Micro and Macro-Analytic Investigation of Intention Execution and Ongoing
Task Cost

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TABLE OF CONTENTS

ACKNOWLEDGEMENTS	iii
LIST OF TABLES	vi
LIST OF FIGURES	vii
LIST OF SYMBOLS AND ABBREVIATIONS	ix
SUMMARY	x
CHAPTER 1: INTRODUCTION	1
Prospective Memory Performance in the Laboratory	2
Experimental Tradition of Prospective Memory Performance	3
Additional Considerations: Ongoing Task Costs and Monitoring	6
Working Memory Capacity and Prospective Memory Performance	7
Attention Control and Ongoing Task Performance	10
Deconstructive Executive Function Account of Prospective Memory Performance	14
Fluid Intelligence, Working Memory Capacity, and Prospective Memory	15
CHAPTER 2: METHODOLOGY	22
Participants	22
Tasks	22
Working Memory Capacity	22
Automated Operation Span	22
Automated Symmetry Span	23
Automated Rotation Span	23
Attention Control	23
Antisaccade	23
Flanker	24
Visual Arrays	24
Fluid Intelligence	25
Ravens Advanced Progressive Matrices	25
Letter Sets	26
Number Series	26
Prospective Memory Tasks	26
Lexical Decision Task	27
Symmetry Judgement Task	28
Odd-Even Judgement Task	28
Ongoing Task Analyses	29
Reaction Time Difference Scores	29
Binning	30

CHAPTER 3: RESULTS	32
Prospective Memory Performance	32
Exploratory Factor Analysis	35
Confirmatory Factor Analysis	36
Working Memory Capacity and Prospective Memory Performance	40
Fluid Intelligence and Prospective Memory Performance	41
Fluid Intelligence and Working Memory Capacity	42
Maintenance and Disengagement in Prospective Memory Performance ..	43
Attention Control Mediation	45
Ongoing Task Performance	52
CHAPTER 4: DISCUSSION	61
APPENDIX A	70
Models with a Single Non-focal Prospective Memory Factor	70
Working Memory Capacity and Non-focal Prospective	
Memory Performance	70
Fluid Intelligence vs. Working Memory Capacity	71
Maintenance and Disengagement in Prospective Memory Performance ..	72
APPENDIX B	74
Models with a Single Focal Prospective Memory Factor	74
Focal Prospective Memory Performance	74
APPENDIX C	77
Flanker Deadline Procedure	77
REFERENCES	78

LIST OF TABLES

Table 1	Descriptive Statistics for All Tasks	32
Table 2	Correlations Between All Tasks	34
Table 3	Exploratory Factor Analysis on Prospective Memory Tasks	35
Table 4	Descriptive Statistics for Ongoing Tasks	53
Table 5	Ongoing Task Accuracy Costs	55
Table 6	Descriptive Statistics for Speed-Accuracy Tradeoff Bin Scores	56
Table 7	Comparing Focal and Non-focal Bin Scores	57
Table 8	Bin Score Correlations	58

LIST OF FIGURES

Figure 1	Contributions of WMC and Gf to PM to Reading Comprehension	17
Figure 2	Maintenance, Disengagement, and Reading Comprehension	17
Figure 3	An Example of an Antisaccade Trial	23
Figure 4	Stimuli Used in the Flanker Task	24
Figure 5	Examples of Visual Arrays Trials	25
Figure 6	An Example Problem from RAPM	26
Figure 7	Example of a focal Lexical Decision Task Run	27
Figure 8	Example of a Non-focal Symmetry Judgement Task Run	28
Figure 9	Example of a Focal Odd-Even Judgement Task Run	29
Figure 10	CFA for All Tasks with Two PM Latent Factors	38
Figure 11	CFA for All Tasks with Single PM Latent Factor	39
Figure 12	WMC Predicting a Single PM Latent Factor	41
Figure 13	Gf Predicting a Single PM Latent Factor	42
Figure 14	Contributions of WMC and Gf to PM	43
Figure 15	Contributions of Maintenance and Disengagement to PM	44
Figure 16	WMC and Mediation Analysis	47
Figure 17	Gf and PM Mediation Analysis	48
Figure 18	Maintenance, Disengagement, and PM Mediation Analysis	49
Figure 19	FlankerDL Maintenance and Disengagement Mediation Analysis	51
Figure 20	Gf Predicting Odd-Even PM Task Bin Score	59
Figure 21	Gf and Odd-Even PM Task Bin Score Mediation Analysis	60

LIST OF FIGURES CONTINUED

Figure A1	WMC Predicting NF PM Latent Factor	70
Figure A2	Gf Predicting NF PM Latent Factor	71
Figure A3	Contributions of WMC and Gf to NF PM	72
Figure A4	Contributions of Maintenance and Disengagement to NF PM	73
Figure B1	WMC and Gf Independently Predicting F PM	74
Figure B2	Contributions of WMC and Gf to F PM	75
Figure B3	Contributions of Maintenance and Disengagement to F PM	76

LIST OF SYMBOLS AND ABBREVIATIONS

AC	Attention control
ACC	Accuracy
ASaccade	Antisaccade task
CFA	Confirmatory factor analysis
EFA	Exploratory factor analysis
F	Focal prospective memory condition
Gf	Fluid intelligence
LDT	Lexical decision task
LetSet or LetterSet	Letter sets task
NF	Non-focal prospective memory condition
NumSeries	Number series task
OE	Odd-even judgement task
OSpan	Operation span task
PM	Prospective memory
RAPM	Raven's Advanced Progressive Matrices
RotSpan	Rotation span task
RT	Reaction time
Symm	Symmetry judgement task
SymSpan	Symmetry span task
VArray, VisArrays, or VA4	Visual arrays task
WMC	Working memory capacity

SUMMARY

Laboratory studies of prospective memory have expanded our understanding about circumstances under which individuals maintain and execute a given prospective memory intention. However, it is only recently that efforts have focused on the role of individual differences in prospective memory performance (Brewer et al., 2010). Specifically, the degree to which individual differences in cognitive ability inform ongoing task performance remains under-investigated. Moreover, the ability to measure the very costs that occur when a prospective memory intention is required has been largely limited to reaction-time difference scores, a method of dubious reliability (Cronbach & Furby, 1970). This study used structural equation modeling to better understand prospective memory performance and the cognitive processes that underlie successful retrieval of an intention. Participants were roughly 300 young adults (age 18-35) from the Georgia Institute of Technology and the greater Atlanta community. Individuals completed a series of cognitive tasks and prospective memory tasks with both focal and non-focal conditions. The results of this study showed that, at the latent level, distinctions between focal and non-focal prospective memory conditions are not as independent as experimental studies have suggested. Specifically, both focal and non-focal task performance was predicted primarily by measures of differences in attention control. Ongoing task costs proved to be even less reliable at the latent level, with the only consistent relationships revealed through the use of bin scores. Further, changes in ongoing task performance with the addition of a prospective memory intention were only related to ability in one set of tasks.

CHAPTER 1

INTRODUCTION

Prospective memory, or the ability to remember to perform an action in the future, is an essential component of everyday life. Picking up dry cleaning on your way home, remembering to give a coworker a message, and calling your mother on her birthday are all examples of successful prospective memory performance. Alternately, omitting an email attachment is an all too familiar example of a prospective memory failure. While forgetting an email attachment is annoying, it is easily remedied. However, there are instances in which prospective memory failures have much more dire consequences. For example, pilots must remember to execute a complicated series of control panel responses when they go below 10,000 feet altitude. Scuba divers must remember to surface slowly, even in the face of an emergency. Individuals who rely on life-saving medications must remember to take them at the appropriate time (e.g., before or after eating). Understanding the conditions under which people are more or less likely to successfully or unsuccessfully execute a prospective memory intention can be a matter of life or death.

Prior, to the establishment of the laboratory paradigm of Einstein and McDaniel (1990), studies of prospective memory performance consisted of semi-experimental studies (Meacham & Leiman, 1982; Moscovitch, 1982). Meacham and Leiman for example asked participants in an otherwise unrelated study to remember to send a mailer back a week later. In this case, successful execution of the prospective memory intention of returning the mailer was the only dimension on which performance could be evaluated.

There was no ability, beyond self-report of the individuals, to ascertain the mechanisms by which individuals managed this intention. Did they write a note? Leave the envelope by the door in hopes of seeing it and remembering to mail it? Did they have someone remind them? Did they find that the intention simply came to mind on occasion? Did they spend a substantial amount of time consciously rehearsing the need to perform this action in the future? Are there systematic differences between individuals who remember to return the mailer vs. those who remember but choose to disregard the request?

Prospective Memory Performance in the Laboratory

The laboratory paradigm of McDaniel & Einstein (2000) allows for a more thorough evaluation of the task conditions under which performance varies. The standard paradigm for these studies includes a baseline or control condition in which a task (the ‘ongoing task’) is presented without a prospective memory intention (i.e. a lexical decision task, or a living non-living task). This baseline condition is followed by the same task with the addition of a prospective memory intention. For example, in a living/non-living task, the prospective memory intention may be to respond (e.g. press the ‘q’ key) when you see the word ‘dog’ (the prospective memory target). The inclusion of the baseline condition is critical as it allows for a comparison of the degree to which resources are allocated away from the ongoing task and towards the prospective memory performance. Resource allocation to the prospective memory intention is then measured as a reaction time difference score between the baseline block and one or more blocks that include a prospective memory target. This decrease in speed from the baseline to the prospective memory block is referred to as ‘monitoring’ and is interpreted as a measure

of the amount of resources now being allocated to the prospective memory intention (Einstein & McDaniel, 2000; Harrison et al., 2010 Scullin, 2013; Smith 2003).

Experimental Tradition of Prospective Memory Performance

The experimental tradition from which this laboratory paradigm was based has focused primarily on how task conditions impact prospective memory performance, as well as how prospective memory intentions impact ongoing task performance. Of principal importance is how performance differs on focal tasks compared to non-focal tasks, as well as the degree to which ongoing task performance changes as a function of the addition of a prospective memory intention.

Focal tasks are those in which the processing of the ongoing task stimuli is congruent with the processing of the prospective memory target. For example, in a living/non-living task, the prospective memory target “dog” would be considered focal because dog is a member of the living category. Alternately, if participants were given the prospective memory target of a word that ends in ‘g’, this would be considered a non-focal task condition. There is nothing inherent about whether or not a word ends in the letter ‘g’ that informs whether or not it is living or non-living. Some researchers also consider tasks to be focal when they are in relative visual or action proximity to the ongoing task. Overall, prospective memory performance under focal conditions is higher than under non-focal conditions (Einstein et al., 2005). Additionally, individuals often show increased ongoing task costs in non-focal conditions (Einstein et al., 2005; McDaniel, 2000; see McDaniel & Einstein 2007 for a summary). Increased time on the ongoing task when prospective memory intentions are added is interpreted as increased resource allocation toward the prospective memory intention beyond that required for the

ongoing task. However, the mechanisms for successful retrieval, including the degree to which ongoing task performance is inherently related to prospective memory performance has been strongly debated.

Two theories dominate this area of research, the Preparatory Attention Model (PAM) (Smith, 2003) and the Multi-process Theory of prospective memory performance (McDaniel & Einstein, 2000). According to the preparatory attention model, resource allocation, as evidenced by the slowing of the ongoing task, is always necessary for successful responding to a prospective memory intention. Smith (2003), for example found that even in ‘focal’ tasks, participants consistently slow during the ongoing task as a result of the addition of a prospective memory intention. Moreover, Smith and Bayen (2004) found slowing when an intention was presented, even if a target is never presented.

In contrast, the Multi-process Theory argues that resource demands required for successful prospective memory performance depend on the task conditions. The multi-process theory does not dispute the usefulness of actively monitoring when performing a very demanding ongoing task, but rather posits that other mechanisms can be used. For example, when ongoing task processing is congruent with the processing demands of the prospective memory intention (a ‘focal’ task), or when the target is particularly salient, the intention may ‘spontaneously pop into mind’ (McDaniel & Einstein, 2000). Self-reports of subjects in Einstein & McDaniel, (1990, as well as work by Kavavilshvili & Fisher, 2000) suggest that intentions sometimes come to mind in the absence of conscious effort, an effect referred to generally as spontaneous retrieval (McDaniel & Einstein, 2000).

Whereas the Preparatory Attention Model presupposes active resource allocation is necessary when the target is encountered, the Multi-process Theory suggests spontaneous retrieval processes can occur in response to the prospective memory target rather than as the result of active monitoring on behalf of the participant (McDaniel & Einstein, 2010). Early support for the existence of a retrieval mechanism beyond monitoring comes from successful retrieval in the absence of ongoing task costs (Harrison et al., 2010; McDaniel & Einstein, 2010; Mullet et al., 2013), as well as studies suggesting that the task costs found by Smith and colleagues may be the result of the number of targets used, which in turn increased the ‘monitoring’ response in participants (Scullin et al., 2010). Perhaps most convincingly, recent research has demonstrated relatively spared prospective memory performance in older adults under focal conditions, but not non-focal conditions (McDaniel & Einstein 2010; Mullet et al., 2013).

More recently, the multi-process perspective has been expanded to include the ‘Dynamic’ Multi-process Theory, which not only supports the ability to successfully execute a prospective memory intention in the absence of measureable cost preceding the target, but also finds that participants who successfully responded to the prospective memory target actually engaged in monitoring following the target presentation (Scullin, McDaniel, & Shelton, 2013). In Scullin et al., Participants completed baseline conditions of a living/nonliving task, lexical decision task, and semantic categorization task, and then encoded the prospective memory intention to respond to the words ‘table’ or ‘horse’ if they occurred at any point during the experiment. A series of distractor tasks, questionnaires, and a delay (of 20 minutes to one full session 12-14 hours later), preceded the experimental block of the three task conditions in which the targets appeared once.

Comparisons were made between ongoing task reaction times for the first 50 trials, for the 50 trials preceding the target, and 50 trials following the target. Participants were further categorized based on whether or not they accurately responded to the first target, or by membership to the control condition without an additional prospective memory intention (e.g. hit subgroup, miss subgroup, and control). Participants did not show an allocation of resources to the prospective memory intention in terms of task costs preceding the target, but those who correctly responded (about 50%) did show slowing after the target occurrence while those who missed did not. Moreover, this performance in the miss condition did not differ from individuals who had not received an additional prospective memory intention. These results not only support the existence of spontaneous retrieval processes in the absence of monitoring, but also inform our understanding of how responding to a target can re-allocate attention toward the ongoing task. Additionally, performance for the second target was higher (76%) for those who exhibited this re-allocation, than for those who did not (43%).

Additional Considerations: Ongoing Task Costs and Monitoring

The findings of Scullin, McDaniel, and Shelton (2013) not only support the role of spontaneous retrieval, but also findings by Marsh & Hicks (2006) suggesting that individuals may increase monitoring once they have determined that a target is likely to occur within the context of a current ongoing task. However, these findings are not sufficient to differentiate the type of process that is being implemented at this time, be it increased attention preparatory monitoring (Smith, 2003), or an engagement of retrieval mode (Guynn, 2002), or a tendency towards cautious responding (Horn, Bayen, & Smith, 2011).

Moreover, some evidence suggests that individual expectations regarding the difficulty of the task are the foundation of ongoing task costs in many prospective memory paradigms (Hicks et al., 2005, Rummel & Meiser, 2013). Rummel and Meiser, for example, found that attentional monitoring in both low and high demand prospective memory conditions varied depending on whether or not participants were given information telling them the task would be more or less difficult, suggesting it was not the task itself, but an individual allocation that determined attention monitoring. However, these metacognitive explanations would suggest a direct relationship to performance, which is not always observed (Harrison & Einstein, 2010; Scullin, McDaniel, & Shelton, 2013).

Working Memory Capacity and Prospective Memory Performance

Initial theories regarding monitoring under non-focal task conditions speculated that the primary underlying cognitive mechanism was working memory. Working memory is a system that reflects resources available for active maintenance and processing of information (Baddeley, 1986). Working memory is one of the strongest and most reliable predictors of real world performance and higher order cognition (Daneman & Carpenter, 1980). Daneman and Carpenter, for example, found that measures of short-term memory did not predict reading comprehension. However, the reading span task, a measure of working memory capacity, strongly predicted comprehension. Whereas measures of short term memory concern the amount of information that can be recalled, working memory capacity is measured by tasks which require individuals to maintain information over a processing delay, such as the operation span, rotation span, and symmetry span (Engle et al., 1999; Conway and Engle 2001). In the operation span, for

example, participants perform a series of arithmetic exercises, followed by a letter. These letters must then be recalled in order of initial presentation. These tasks rely heavily on the ability to maintain information over a delay which includes processing demands, and have been linked to processes such as goal instantiation (Meir et al., 2017), and maintenance (Shipstead et al., 2016).

Early correlational studies examining the relationship between working memory capacity and prospective memory performance yielded inconsistent results, with some studies finding this relationship (Cherry & LeCompte, 199; Kliegel, Martin, McDaniel & Einstein, 2002; Reese & Cherry 2002) and others not (Kidder, Park, Hertzog, & Morrell, 1997, Smith 2003, West & Craik, 2001). Part of the discrepancy in early findings was due to a lack of systematic distinction between focal and non-focal conditions (Shelton & Christopher, 2016), but this issue is still debated as it pertains to prospective memory broadly. More often than not, however, evidence generally supports a relationship between working memory capacity and prospective memory performance under demanding processing conditions or instances in which monitoring is advantageous over spontaneous retrieval processes. Below I review two studies that highlight the different outcomes.

In one of the first true systematic studies of individual differences in prospective memory performance Brewer, Knight, Marsh, and Unsworth (2010) used an extreme groups design to compare prospective memory performance in individuals considered to be high in working memory capacity with those low in working memory capacity, under both focal and non-focal prospective memory task demands. Brewer and colleagues administered a series of complex span tasks to their participants and then performed a

quartile split taking the top quarter high and low individuals, and then gave these individuals a prospective memory task with a focal and non-focal condition. There were no group differences in the focal condition. However, in the non-focal condition, high working memory capacity individuals significantly out-performed low capacity individuals. Additionally, while both group showed ongoing task costs, they did not differ on the degree of the costs in the non-focal condition. Taken together, these results support the idea that high working memory capacity individuals are better able to maintain the prospective memory intention in the face of the more demanding non-focal task condition. Moreover, these results support the idea that the control of attention, rather than the amount of attention, is particularly important for successful prospective memory retrieval under non-focal task conditions (Conway et al., 2005).

However, some studies do not find that working memory capacity fully explains differences in non-focal prospective memory performance, suggesting that other mechanisms may also be important. Zeintle, Kliegel, Hofer (2007), for example, found age related effects on prospective but not retrospective memory performance, even after controlling for working memory capacity and speed of processing. Moreover, working memory is not a singular process, but rather a combination of both processing, and maintenance abilities (among others), and the interpretation of its relationship to performance should be tenuous. Additionally, these studies do not inform our understanding of performance under conditions in which individuals differ in their use of spontaneous retrieval processes.

Attention Control and Ongoing Task Performance

According to the executive attention account of working memory capacity of Engle and colleagues, lower order attentional processes account for a significant proportion of the working-memory-capacity-related differences in higher order cognitive abilities. Attention control is in essence the guiding force which aids in the continued activation of material in the working memory system (Conway & Engle 2001; Engle et al., 1999). Subsequently, working memory capacity and attention control are sometimes, and erroneously, used interchangeably when explaining individual differences in prospective memory performance. The two constructs are not identical, and as such should be treated differently with regard to the types of performance variance they capture. A recent study by Meier et al., (2017) for example, argues that the relationship between working memory capacity and the anti-saccade task (which is frequently the anchoring task in factors of attention control), is specifically related to goal instantiation, and not maintenance, or resistance to mind wandering.

Further, the role of attention is commonly speculated through the use of working memory capacity measures is primarily emphasized when describing monitoring processes during the ongoing task, rather than successful execution of prospective memory intentions. Specifically, many studies attempt to interpret the degree to which attention is differentially allocated to either the prospective memory intention or the ongoing task, based on differences in reaction time once a prospective memory intention is added to another task.

Initially, it was assumed that prospective memory tasks functioned similarly to a dual task, in which participants needed to determine the extent to which attention would

be given to one task or the other. Subsequently, changes in the attention allocation towards the prospective memory intention would be reflected in ongoing task reaction time scores (Smith, 2003). This view assumes the attention resource is a singular, relatively static entity that must be divided such that the degree to which the prospective memory intention moved resources away from the ongoing task can be ascertained by looking at changes in reaction time from the control block to the prospective memory block. Additionally, these early measures of cost also base their interpretations of resource allocation based solely on the use of reaction time difference scores which is inherently problematic (Chronbach & Furby, 1970). However, as our understanding of instances in which ongoing task costs are impacted by the prospective memory intention (Scullin et al., 2010) or altered in response to perceived task demands (Rummel et al., 2016), attempts to differentiate constant as opposed to transient attention allocation have become more complex in nature.

For example, some recent investigations into the unity of the resource or ‘attention’ allocation to the ongoing task have used an ex-Gaussian distribution to measure fluctuations in attention. The dual parameters of the model allow for some considerations of sustained vs transient attentional focus to the ongoing task (Ball, Brewer, Loft, & Bowden, 2015). For each time point in a series x , the ex-Gaussian distribution is described by the mean (μ) and the variance of the Gaussian distribution, and the mean (and standard deviation) of the exponential distribution (t). Thus the sum of the μ and t parameters equal the mean of the overall distribution, and is approximately equal to the mean reaction time. A distributional shift to the right reflects an increase in μ , whereas a positive distributional skew reflects an increase in t (Balota & Yap, 2011).

Although these parameters are not linked to specific cognitive processes, research regarding manipulation effects suggests that the parameters are impacted more by some manipulations than others. For example, a positive skew to the tail has been shown to reflect goal neglect or attentional lapses (Schmiedek et al., 2007; Tse, Balota, Yap, Duchek, & McCabe, 2010). In the context of prospective memory, we would expect changes in μ , when a prospective memory intention is being maintained, with more sporadic changes reflected in the t parameter (Guynn, 2003; Scullin et al., 2013).

Brewer (2011), for example, found that the measurement of ongoing task interference captured by reaction time difference scores in a non-focal condition were not related to sustained attentional processes which would be captured in μ , but rather by the frequency of slow responses captured by fluctuations in t , reflecting momentary lapses in attention, or mind wandering. However, it was not possible to infer from these findings whether the increase in t was reflective of increased focus, or lapses in attention.

Rummel, Smeekens, & Kane (2017) also used an ex-Gaussian distribution in their study of mind wandering, attention, and prospective memory performance. Kane et al., found that the addition of any prospective memory intention not only interfered with ongoing task processing, but also reduced the number of task unrelated thoughts (TUTs). Participants experience significantly fewer TUTs when they are given rewards for their performance, suggesting that the addition of a prospective memory intention increases attentional awareness to both the ongoing task and the prospective memory intention. These findings support underlying ideas of the PAM, as well as Marsh et al. (2005), in so much as resource allocation, in the form of increased attention, and subsequent task

activation, is more or less inherently increased in all prospective memory tasks in which a target is anticipated.

There is not, however, a consensus regarding whether attention allocation reflected in these parameters is based on individual differences in cognition or if it is subjectively allocated by the subjects, or more of a metacognitive awareness adjustment based on increasing tasks demands. Rummel et al. (2017), suggested that ongoing task performance is due less to attention orientation or cognitive ability, than to a person's preferred response criterion with a prospective memory intention added.

Additionally, the Rummel et al., (2017) finding regarding increased attention towards the prospective memory task, as well as the increase in transient shifts found in Ball et al. (2015) bring us to an interesting point regarding ongoing task performance. Specifically, higher ability individuals often show a slowing of a task following an error, which lower span individuals do not (Draheim, Hicks, & Engle, 2016). Thus, it is possible that these longer reaction times do not necessarily reflect re-activation of the goal (of responding to a prospective memory target), but could in fact reflect a reorientation towards the ongoing task. Thus, errors are beneficial in reactivating the task set in high working memory capacity individuals, but low working memory capacity individuals do not experience this same effect. Moreover, they are more likely to experience general task unrelated thoughts which are in turn reflected by occasional longer response times.

To date, the majority of the work regarding ongoing task performance emphasizes the use of reaction time scores and reaction time difference scores which are highly unreliable in nature. Further, the majority of these studies do not include multiple

indicators of cognitive abilities, and subsequently cannot speak to the degree to which individuals of differing cognitive ability vary in their adaptations to added prospective memory task demands. However, when they do, they show that the ability to resist intrusions in these tasks is independent of both working memory capacity and sustained attention (Rummel et al., 2017).

Deconstructive Executive Function Account of Prospective Memory Performance

Based on this to-be-accounted-for variance, a collection of studies have attempted to isolate the contributions of executive functions such as shifting, updating, and inhibition (Friedman et al., 2004; Miyake et al., 2000) to prospective memory performance (Gunnead et al., 2010; Marsh & Hicks, 1998, Martin et al., 2003; Zuber et al., 2017). However, many of these studies use an ongoing task load manipulation, rather than adjusting the congruency between target and ongoing task processing, ultimately circling back to a suggestion regarding the role of executive functions in attention tasks, broadly defined.

Zuber et al. (2017), for example, examined the role of updating, inhibition, and shifting with respect to both focal and non-focal prospective memory performance. Latent variables for the prospective memory conditions were created using a split half procedure. Zuber and colleagues found a relationship between updating and inhibition to focal prospective memory performance, and shifting only to non-focal (updating and inhibition were not related to focal performance). However, these results are somewhat difficult to interpret due to the structure of the prospective memory task.

Specifically, participants performed a 2-back rating of white upper case letters. In the focal condition, the target was the appearance of an 'A' or a 'D'. However, for the

non-focal condition, participants had to respond to a specific color of box on the screen surrounding the letter. In other words, in the focal condition, the target was found within the ongoing task, and was salient insofar as the processing of the target was congruent with the ongoing task. In the non-focal condition, the prospective memory target is not only not focal, it is not even processed in the context of the ongoing task. Subsequently, this task comparison is more of a comparison of a focal task and a dual-task in which attention must be consciously shifted away from the ongoing task. Therefore, it is not surprising that shifting was important, or that updating was related to focal performance, as one of the measures was the ongoing task in this condition.

Subsequently, results of studies that attempt to identify the role of specific executive functions as they relate to performance are inconsistent at best (Gunnead et al., 2010). I will argue that the primary function of the majority of the executive functions included in these studies can be traced to the ability to manage task irrelevant information. For example, in Zuber et al., (2017) the ability to ignore the colored boxes around the letter in the N-back task is beneficial for performance. Subsequently, it is possible that the variance captured by the measures of updating and inhibition is better described by the ability to resist interference from unrelated stimuli, rather than the ability to focus attention towards the ongoing task or the prospective memory intention. Moreover, it is possible that this ability to resist intrusions may be best represented by processes reflected in fluid intelligence.

Fluid intelligence, Working Memory Capacity, and Prospective Memory

Fluid intelligence is the ability to reason with novel information in order to solve complex problems (Horn & Cattell, 1966). Fluid intelligence tasks are very highly

correlated with complex span measures of working memory capacity, with correlations as high as .85 (Kane, Conway, & Hambrick, 2005). However, this relationship is not perfect. One explanation for this high, but not perfect relationship is that fluid intelligence measures capture additional variance that is best described as disengagement (Shipstead et al., 2016). For example, in fluid intelligence tasks such as the Ravens Progressive Matrices, participants must decide which piece comes next in a series. To determine the answer, participants must not only activate, maintain, and manipulate information mentally in order to solve the problem (all components of complex span tasks), they must also let go of, identify as irrelevant (Oberaur et al., 2007), remove from focus (Ecker, Lewandowsky, & Oberauer, 2014), inhibit (Hasher & Zacks, 1988), etc. solution patterns that no longer serve their purpose. Failure to do so results in perseverations, an action detrimental to performance in timed tasks (as measures of fluid intelligence are).

Evidence suggests that disengagement is a process that is not just fluid intelligence specific, and can be observed in other tasks in which no-longer relevant information must be released, such as updating (Martin, et al., submitted). Martin et al. performed a modeling series in order to isolate the relationship between fluid intelligence and working memory capacity as they relate to reading comprehension.

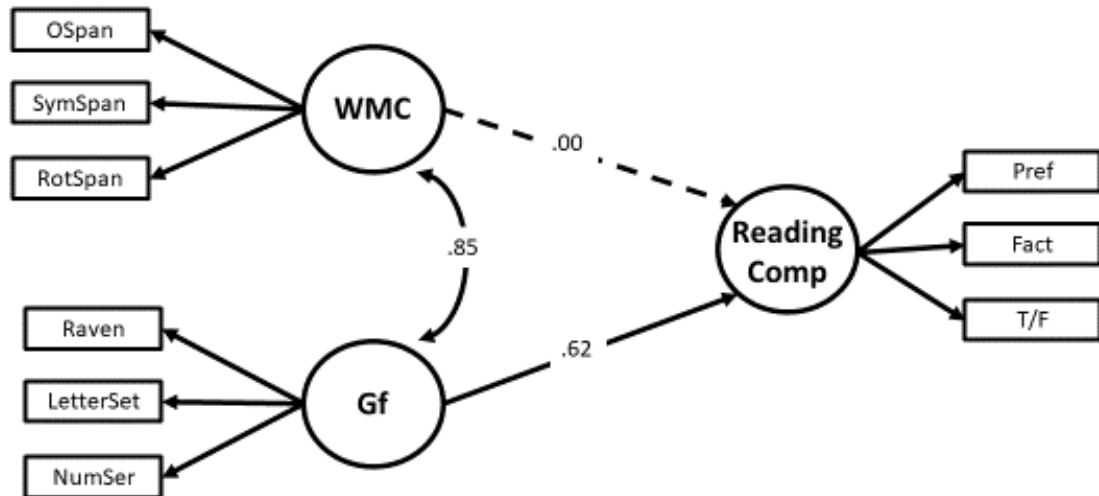


Figure 1. Contributions of WMC and Gf to reading comprehension. Reprinted with permission from Martin et al., (submitted). Abbreviations as follows: WMC= working memory capacity; GF= fluid intelligence; Reading Comp =reading comprehension.

First, fluid intelligence and working memory capacity were compared directly, with fluid intelligence capturing all of the variance in reading comprehension (figure 1).

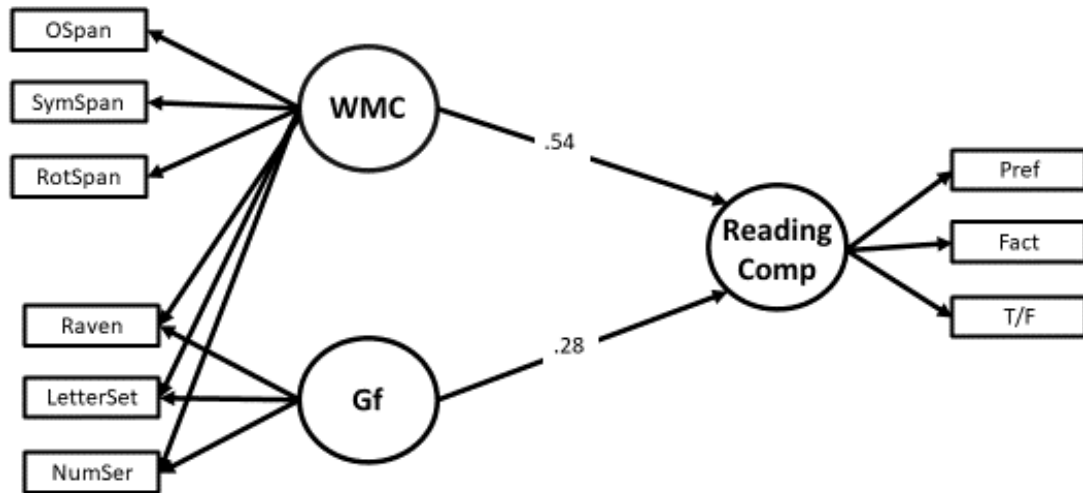


Figure 2. Contributions of maintenance and disengagement to reading comprehension. Reprinted with permission from Martin et al., (submitted). Abbreviations as follows: WMC = working memory capacity; GF = fluid intelligence; Reading Comp =reading comprehension.

Next, the fluid intelligence tasks were cross-loaded onto the working memory capacity factor, in essence pulling all of the shared variance (maintenance) onto the working memory factor. This resulted in two significant paths, one primarily reflecting shared variance related to ‘maintenance’, and the second, a residual fluid intelligence factor primarily reflecting ‘disengagement’ (figure 2).

There is some explicit evidence of the importance of fluid intelligence to prospective memory performance, beyond its relationship to working memory capacity. A meta-analysis by Utzl (2011) showed that the association between prospective memory and verbal intelligence was strong enough to explain why some studies of prospective memory and aging failed to find age declines in prospective memory; he found that the verbal intelligence advantage of older adults over younger adults was moderately ($r = -0.49$) correlated with the size of age declines. However, much less work has examined the relationship between fluid intelligence and prospective memory performance in younger adults.

Additionally, given the strong relationship between working memory capacity and performance in non-focal tasks, it is possible that studies finding a relationship between working memory capacity and prospective memory performance are in fact capturing a subset of variance related to fluid intelligence. Moreover, if fluid intelligence captures a substantial amount of variance in performance beyond working memory capacity, then it suggests that these additional ‘disengagement’ processes may also be important for successful prospective memory retrieval, and may reflect some of the additional variance not accounted for by working memory capacity, sustained attention, or processing speed (Rummel et al., 2017, Meier et al., 2017).

A significant relationship between working memory capacity and fluid intelligence would be valuable in linking the role of maintenance and disengagement processes to prospective memory performance, as well as supporting current findings with tasks that encompass substantially more method variance than comparing executive function or complex span tasks and prospective memory tasks.

Additionally, just as the relationship between working memory capacity and fluid intelligence is not perfect, neither is the relationship between attention control and working memory capacity. Specifically, with regard to the role of maintaining information (as opposed to goal activation as suggested by Meier et al. (2017)) it may be possible to separate out the functions of attention control and working memory capacity as they relate to performance in both focal and non-focal conditions, by examining their shared and independent contributions at the latent level. Subsequently, we will refine our understanding of the role of attention control in prospective memory performance by testing its influence at the latent level. Theoretically it is possible that attention control is a sufficient predictor of prospective memory performance that no further ‘ability’ identifier such as working memory capacity or fluid intelligence is needed to predict performance.

Further, current measures of resource allocation when a prospective memory intention is added do not take adjustments beyond reaction time into consideration. In other words, using reaction time difference scores, or even ex-Gaussian analyses to interpret resource or attention allocation do so to the exclusion of more broad-based task adjustments such as a speed/accuracy tradeoff. In general, participants do consistently slow to non-focal task demands and not to focal, suggesting some internal recognition

that one task is subjectively less resource demanding than the other, even if they are not aware of the reasons. However, ongoing task accuracy is seldom reported, and to date, no attempts have been made to measure the degree to which speed and accuracy are impacted by prospective memory demands, or differentially so based on cognitive ability measures. Subsequently, we will include an adapted version of the Hughes, Linck, Bowles, Koeth, and Bunting (2014) binning procedure in which speed and accuracy are combined to create a score reflecting the speed accuracy tradeoff for each individual, based on type of prospective memory demands. This will allow us to evaluate whether this adjustment is related to cognitive ability, task demands, or personal preference.

In summary, systematic studies of prospective memory have expanded our understanding about circumstances under which individuals are likely, or not, to maintain and execute a prospective memory intention. However, the role of individual differences in prospective memory performance, is less defined, as is the degree to which these individual differences relate to difference in ongoing task performance. Results of this study answer the following questions:

- 1) Is prospective memory capacity a unitary factor at the latent level when a variety of tasks are used?
- 2) Do the relationships between working memory capacity and fluid intelligence and prospective memory performance differ when prospective memory tasks are focal or non-focal in nature?
- 3) Is the relationship between fluid intelligence and performance stronger than that of working memory capacity and performance?

- 4) Do the processes of maintenance and disengagement outlined by Shipstead, Harrison, and Engle (2016) independently predict prospective memory performance?
- 5) Does attention control mediate the relationship between these higher order ability constructs and performance?
- 6) Does the use of bin scores provide a more accurate description of ongoing task 'costs' across diverse task sets than the use of reaction time difference scores?
- 7) Are ongoing task costs related to ability?

CHAPTER 2

METHODOLOGY

Participants

Participants were 296 younger adults (aged 18-35) from the Georgia Institute of Technology and extending to the greater Atlanta community. They were recruited through SONA, as well as through flyers on campus, targeted advertisements on Facebook, and ads in Creative Loafing. Participants received compensation in the form of course credit or \$15 per hour (8 total hours), with a \$10 completion bonus. Individuals were excluded if they were missing more than one full set of tasks. Missing data was imputed only for latent variable analyses.

Tasks

Working Memory Capacity

Automated Operation Span (OSpan; Unsworth, Heitz, Schrock, Engle, 2005). The OSpan is a complex span task, so named because two simpler tasks are combined into an alternating dual task. Test-takers must recall a series of serially presented items, the presentation of which is interrupted by a simple processing task. For the OSpan the to-be-remembered items are letters from the English alphabet. The processing task is a simple mathematical equation that must be solved before the next letter of a sequence is presented. Lists lengths vary between 3-7 items. The list lengths were presented in a randomized order, with the constraint that a given length cannot repeat until all lengths had been presented. Each list length was used three times. The dependent variable was the number of letters recalled in proper serial position during the session (i.e., partial scoring method).

Automated Symmetry Span (SymSpan; Unsworth, Redick, Heitz, Broadway, & Engle, 2009). The SymSpan is a complex span task. The to-be-remembered items were spatial locations in 4×4 grid. The processing task required test-takers to judge whether or not a figure in an 8×8 grid is symmetrical. List lengths were 2-5 items. Other characteristics mirrored the Ospan.

Automated Rotation Span (RotSpan; Harrison et al., 2013). The RotSpan is a complex span task. The to-be-remembered items were a sequence of long and short arrows, radiating from a central point. The processing task required test-takers to judge whether a rotated letter is forward facing, or mirror-reversed. List lengths were 2-5 items. Other characteristics mirrored the Ospan.

Attention Control

Antisaccade (Kane et al., 2001; Unsworth et al. 2004). The participant fixates a small cross at the center of the screen. After a 400 to 500 ms interval, a star flashes on one side of the cross for 250 ms. After a 150 ms interval, a *Q* or an *O* is presented for 250 ms at the opposite side of the screen; the participant's task was to identify the letter. A total of 48 stimuli were presented.

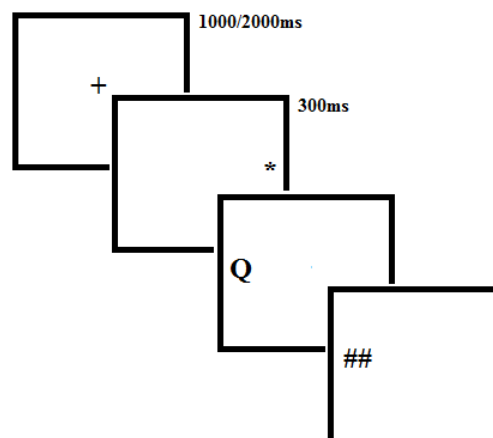


Figure 3. An example of an Antisaccade trial.

Flanker (Erickson, 1978). Participants were presented with three left or right-facing arrows at the center of the screen; one is the target arrow, in the center, flanked by two distractor arrows, which either pointed in the same direction as the target arrow (congruent condition) or in the opposite direction (incongruent condition). Participants report the direction indicated by the target arrow. The participant's score was their response time for the incongruent condition with RT for the congruent condition subtracted.

→→→→→ Congruent

-- → -- Neutral

→→←→→ Incongruent

Figure 4. Stimuli used in the Flanker Task

Visual Arrays (Luck & Vogel, 1997). Participants saw an array of blue and red rectangles differing in orientation. Prior to each trial, the participants were cued to attend to either the red or blue rectangles. Next, the array was presented for 250 ms. after a delay of 900 ms, the array presented again, with one of the rectangles highlighted by a white dot; this rectangle changed orientation on 50% of the trials. The participant judged whether the rectangle had changed orientation or not. Array sizes used were 5 and 7 items per color. A total of 48 trials were presented for each array size. The participant's score was proportion of trials answered correctly.

Although this task is not traditionally included in attention control batteries, evidence suggests that it is in fact an attention control measure due to its relationship to

the anitisaccade task (Martin & Verhaeghen, submitted; Shipstead et al., 2016). As such, it was included both to continue to examine its usefulness as a measure of attention control, as well as to strengthen our attention control factor by adding a task that makes use of accuracy rather than reaction time difference scores.

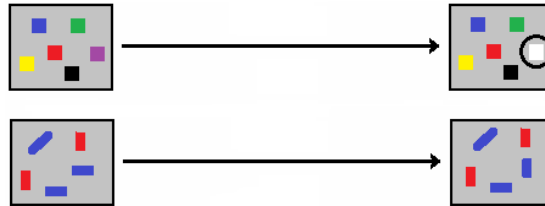


Figure 5. Examples of Visual Arrays trials.

Fluid Intelligence

For all fluid intelligence tasks, the dependent variable was the number of correct responses provided within the allotted time.

Raven's Advanced Progressive Matrices (RAPM; Raven, 1990; Odd problems). On each trial, eight abstract figures were embedded in a 3×3 matrix. The final position in the matrix was blank. Test-takers selected one of several options completed the sequence. Ten minutes were given to solve 18 problems.

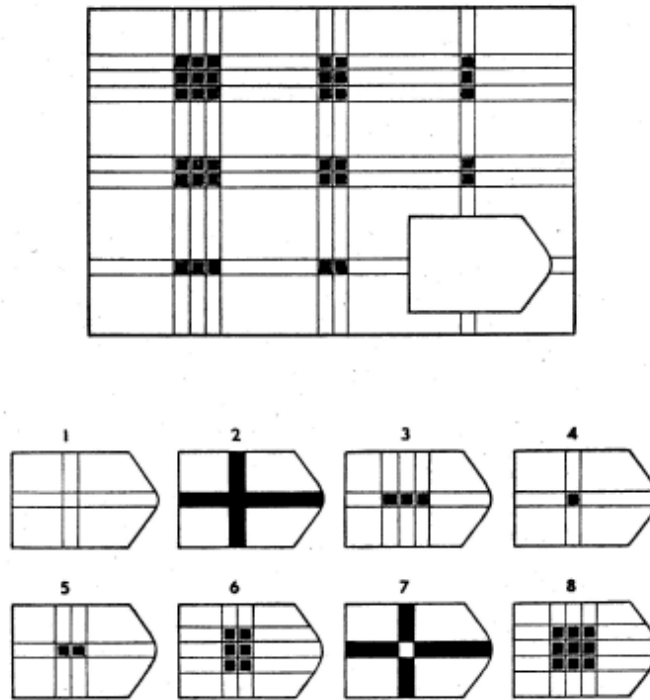


Figure 6. An example problem from Raven's Advanced Progressive Matrices.

Letter Sets (LetterSet; Ekstrom et al., 1976). On each trial, five four-letter strings were presented. Four of the sets followed a specific rule. The test-taker needed to discern this rule and decide which string did not follow it. Seven minutes were given to complete 30 problems. The dependent variable is the number of correct responses.

Number Series (NumSer; Thurstone, 1938). A series of numbers were presented on a computer screen. A rule joined these numbers. The test-taker needed to discern this rule and decide which number was next in the sequence. Five minutes were given to complete 15 problems. The dependent variable was the number of correct responses.

Prospective Memory Tasks

Three different prospective memory tasks were included, each with a control, focal, and non-focal condition. All items, including the target were be repeated 4 times.

Each experimental condition (focal and non-focal) contained 4 blocks of 70 trials, with the prospective memory target occurring on trial 70. The experimental conditions were preceded by a 30 trial practice block, and a 280 trial control block. The order of presentation of experimental block was counter balanced across participants with half receiving the focal block following the control block, and half receiving the non-focal block following the control block. For all tasks the prospective memory intention was to press the 'q' key whenever participants encountered a target item. All other responses were made on the number pad on the opposite end of the keyboard from the 'q' key.

Lexical Decision Task. Participants received a string of letters and identified whether or not they formed a word. The focal prospective memory target were the words 'dolphin' and 'pyramid', the non-focal target was be a string ending with the letter 'g' (one word and one non-word).

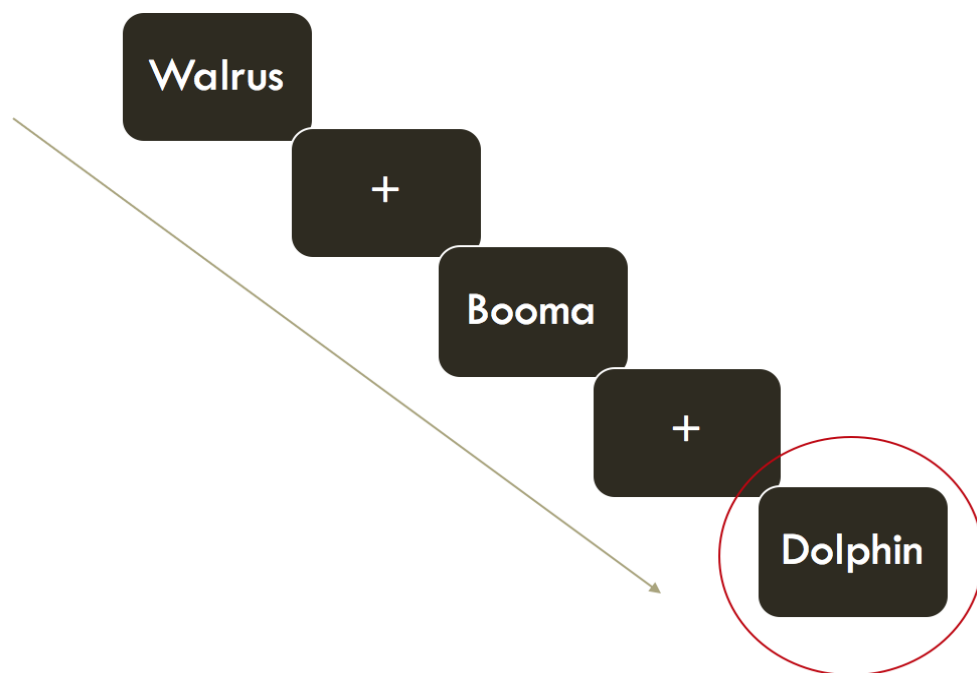


Figure 7. Example of a focal lexical decision task run.

Symmetry Judgment Task. Participants identified whether a presented image was symmetrical about the vertical axis. The focal prospective memory intention was to respond when an image was circular in nature. The non-focal intention was to respond when a box in the corner turns green (it rotated through colors and locations).

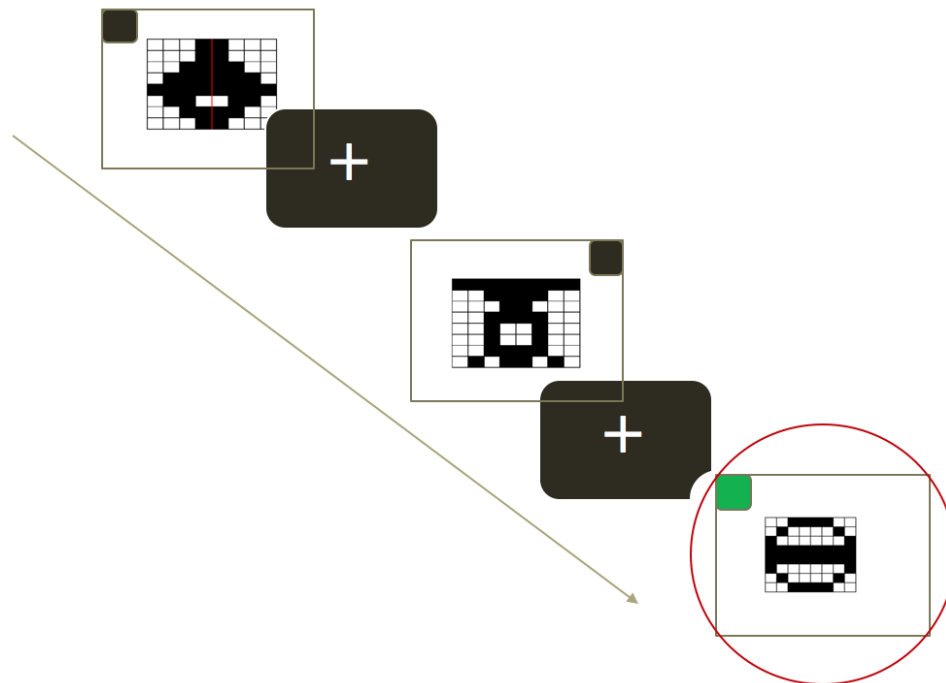


Figure 8. Example of a non-focal symmetry judgement task run.

Odd-Even Judgment Task. Participants were asked to decide if a number (1-9) was odd or even. Numbers were presented in different colors, with a colored box surrounding them as well. The focal prospective memory target was a yellow number, and the non-focal was a red box surrounding the number. Although the processing of the focal condition is incongruent with the identification of the number as odd or even, the ongoing task is the easiest of the three. This also allowed for a comparison of tasks in which

processing is incongruent, vs saliency being incongruent. As the focal stimulus is still very salient to the ongoing task, and the non-focal target is not.

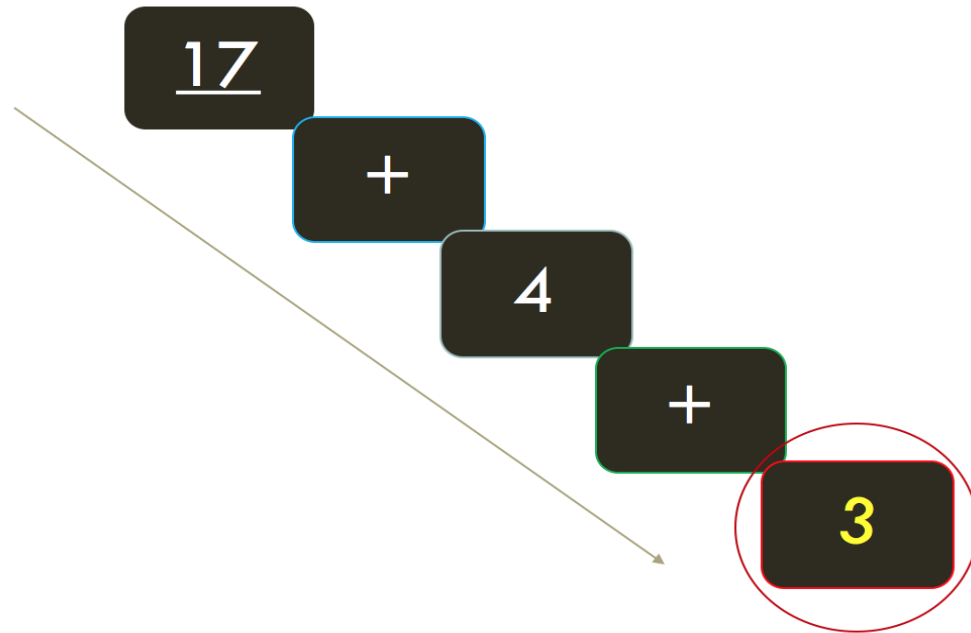


Figure 9. Example of a focal odd-even judgement task run.

Ongoing Task Analyses

Ongoing task performance was analyzed using both traditional reaction time difference scores and an adaptation of the Hughes et al. (2014) binning procedure.

Reaction time difference scores.

Ongoing task costs were measured, as many studies have done, by subtracting the average reaction time of all correct responses from each prospective memory condition, from the average reaction time of correct responses from the baseline condition. Further, reaction time difference scores were incorporated which include inaccurate trials as well

in order to provide a reaction time difference measure which does not only focus on accurate trials.

Binning.

Binning allows for the assessment of the speed accuracy trade off within a task (Hughes, Linck, Bowles, Koeth, & Bunting, 2014). We used an adaptation of the binning procedure to evaluate the degree of the speed accuracy adjustment made from the baseline to the focal condition, and the focal to then non-focal condition.

Bin scores from this procedure are traditionally calculated in the following manner:

1. Calculate mean RTs on *accurate nonswitch trials* (by subject).
2. Subtract this Mean RT from the RT for *each* subject's individual *accurate switch* trial.
3. Rank order the RT difference scores from step 2 for each subject into deciles (i.e. bins with a value of 1-10, with the fastest scores in bin 1, and slowest in bin 10). This results in every accurate switch trial having a corresponding bin value of 1-10.
4. Assign all inaccurate switch trials a bin value of 20 (any number will suffice here).
5. Sum all respective bin values for each subject, to compute a single bin score for each individual.

A smaller bin score for a subject indicates a combination of two things:

1. Participant's RTs on accurate switch trials were only slightly larger than for non-switch trials.
2. The subject made fewer errors on switch trials than other subjects.

Thus, the binning method incorporates both reaction time and accuracy data from the task into one comprehensive score, and provides more information than traditional techniques that either ignore one of the two measures or attempt to analyze them separately. This method was also shown to have high reliability in Hughes et al. (2014) in their two experiments, whereas both latency and accuracy switch costs had low reliability.

In order to perform this adaptation of the binning procedure (which was initially used on task switching procedures) the control trials served as the non-switch trials, and the prospective memory trials served as the non-switch (calculated independently for the focal and non-focal conditions). In this procedure, individuals are rank ordered based on reaction time to correct trials, and also penalized for incorrect trials, thus allowing for a measure of ongoing task performance adjustments that incorporates both speed and accuracy.

CHAPTER 3

RESULTS

Prospective Memory Performance

Descriptive statistics for all cognitive measures and prospective memory conditions are reported in Table 1.

Table 1. Descriptive statistics for all tasks.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
RAPM	265	1	18	10.56	3.193
NumberSeries	265	2	15	10.00	2.947
LetterSets	265	5	28	17.30	4.268
OSPAN	265	1	82	56.01	15.705
SSPAN	265	3	52	27.55	10.362
RotSPAN	265	0	62	25.57	10.686
Flanker	265	-9.986	271.146	81.99807	43.553663
Antisaccade	265	.361	1.000	.79617	.148602
VA4	265	-1.300	5.325	1.82781	1.219207
OEFocal.PM.ACC	255	.00	4.00	2.0282	1.51693
OENF.PM.ACC	255	.00	4.00	2.0939	1.50803
SymmFocal.PM.ACC	276	.00	4.00	3.5399	.94688
SymmNF.PM.ACC	276	.00	4.00	2.6775	1.35687
LDTFocal.PM.ACC	265	.00	4.00	2.4221	1.35938
LDTNF.PM.ACC	265	.00	4.00	1.5627	1.34606

Note. Task abbreviations are as follows: RAPM=Ravens progressive matrices; LetterSet=Letter set task; NumSeries= number series task; OSpan=operation span; SymSpan=Symmetry Span; RotSpan= rotation span; VA4= visual arrays; ASaccade= anti-saccade ;PM = number of targets identified precondition; LDT.F= accuracy to prospective memory targets in the focal lexical decision prospective memory condition; Odd/Even.F = accuracy to prospective memory targets in the focal odd-even judgment task; Symm.F = accuracy to prospective memory targets on the focal symmetry judgment task; LDT.NF= accuracy to prospective memory targets in the non-focal lexical decision prospective memory condition; Odd/Even.NF = accuracy to prospective memory targets in the non-focal odd-even judgment task; SymmNF = accuracy to prospective memory targets on the non-focal symmetry judgment task.

Table 2 shows correlations between all tasks used for latent variable analyses. Note that the odd-even tasks and the focal symmetry judgment tasks correlated well with each other. Overall relationships between individual prospective memory tasks and cognitive ability tasks were inconsistent, with the exception of relationships to the antisaccade. No consistent trend was observed between focal tasks and ability or non-focal tasks and ability overall.

Table 2. Correlations between cognitive measures and prospective memory performance in all conditions. Significant values ($p < .05$) are in bold.

	RAPM	NumberSeries	LetterSets	OSPAN	SSPAN	RotSPAN	Flanker	Antisaccade	VA4	OEFOcc. PMACC	OENFPM. ACC	SymmFoc alPM. ACC	SymmNF. PMACC	LDTFoc. PMACC	LDTNF. PMACC
RAPM	1														
NumberSeries	.474	1													
LetterSets	.474	.478	1												
OSPAN	.351	.260	.310	1											
SSPAN	.401	.275	.278	.567	1										
RotSPAN	.394	.393	.405	.393	.554	1									
Flanker	.155	-.054	.137	-.042	.137	.149	1								
Antisaccade	.396	.319	.352	.291	.319	.389	.123	1							
VA4	.376	.350	.323	.255	.378	.392	.162	.425	1						
OEFOcc.PMACC	.231	.242	.202	.048	.179	.272	-.066	.176	.188	1					
OENFPMACC	.217	.179	.135	-.051	.113	.174	-.081	.276	.306	.393	1				
SymFoc.PMACC	-.103	.109	.005	-.002	.007	.047	.071	.064	.074	.148	.187	1			
SymmNF.PMACC	.117	.075	.066	-.025	-.046	.088	-.038	.148	.051	.213	.265	.327	1		
LDTFoc.PMACC	.236	.076	.127	.029	.137	.175	-.053	.142	.234	.216	.100	.053	.217	1	
LDTNF.PMACC	.091	.068	.060	-.054	.064	.030	.132	.140	.119	.280	.383	.075	.154	.103	1

Exploratory Factor Analysis

Table 3 shows an exploratory factor analysis (EFA) that suggested a single prospective memory factor based on eigenvalues >1 . Although a two factor solution was anticipated, all model analyses strongly suggested a single prospective memory latent variable. The loadings presented in table 3 show the factor loadings by task. The only loading which is less than .4 is the focal lexical decision task. All other tasks load relatively equally on the single prospective memory factor, based on the exploratory factor analysis. Next a confirmatory factor analysis (CFA) was run to verify the existence of a single or two prospective memory latent factors.

Table 3. Results from the exploratory factor analysis on the prospective memory tasks.

Factor Matrix ^a	
	Factor 1
SymmFocal.PM.ACC	.473
SymmNF.PM.ACC	.534
LDTFocal.PM.ACC	.350
LDTNF.PM.ACC	.489
OEFocal.PM.ACC	.598
OENF.PM.ACC	.674

a. 1 factors extracted. 4
iterations required.

Note. Goodness-of-fit values: Chi-sq 19.19 (9) $p < .05$. A single factor solution was favored.

For all structural equation models, solid paths represent significant paths and dotted lines represent non-significant paths. The chi square values, degrees of freedom, and chi square significance will be reported. The chi-square assesses overall fit and

discrepancy between the sample and generalized population wide fitted covariance matrices. Although a non-significant chi-square value is preferred, indicating it is not different from a general population model, it is very sensitive to sample size. As such, the chi-square value alone is not sufficient to accept or reject a model. Models must be considered in holistic terms based on multiple fit indices. The following fit indices will be reported as well: The confirmatory fit indices (CFI) and the Root Mean Square Error of Approximation (RMSEA). The CFI compares model fit to a null model and is considered to be a 'good' fit if the CFI is $> .90$. A CFI of over .90 indicates that the model of interest improves fit by 90% relative to a null model. For my purposes we will consider a model with a CFI of .95 or higher to have very good fit. The RMSEA is a parsimony adjusted fit index. Models with an RMSEA $< .08$ are considered to be an acceptable fit, with an RMSEA of .06 or lower considered to be a good fit (Kenny, 2008). All models had good to very good fit based on their model fit statistics.

Confirmatory Factor Analysis (CFA)

A confirmatory factor analysis (CFA) with two prospective memory factors (figure 10) was run first. This model showed 'good' fit, and also a correlation between the two prospective memory factors (focal and non-focal) of .89. Based on the EFA, a second CFA was run in which the path between the two factors was set to 1. If a Chi squared difference test between the two models shows no significant change, then two factors are considered to have a correlation of 1. If the change in Chi square is significant, however, the two factors are considered to be independent. When the path between the two prospective memory factors in this model was constrained to 1, the change in Chi square was not significant. This means that a model containing a single factor is not

significantly different from one containing two prospective memory factors. The lack of change in model fit when this path is constrained to 1 means that the tasks comprising the two factors actually reflect a single factor. This single factor CFA solution further confirmed that the tasks used for this study reflect a single general prospective memory factor at the latent level, rather than a focal and non-focal factor as would be anticipated based on experimental classification.

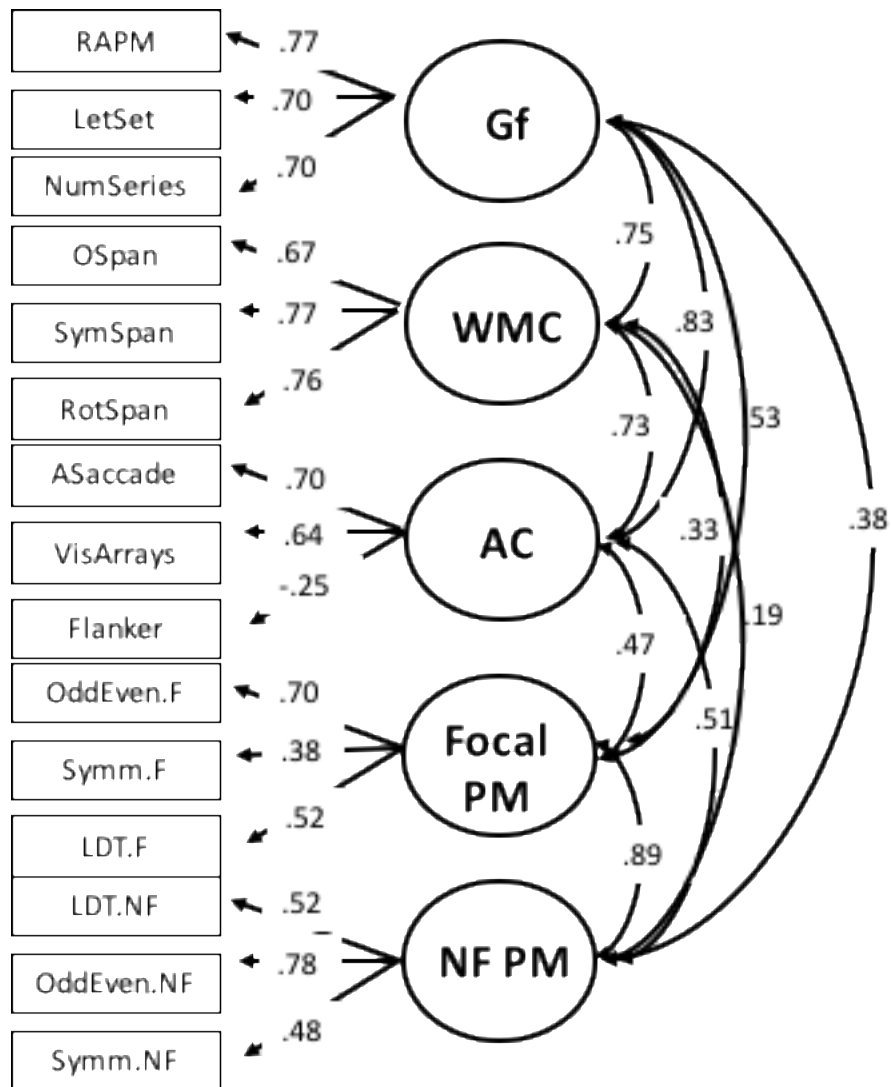


Figure 10. CFA for all tasks with two prospective memory latent factors. Once this path was constrained to zero, no change in model fit was observed. Fit Chi sq = 117.277 (80) $p < .05$; CFI = .97; RMSEA = .04. Task abbreviations are as follows: WMC = working memory capacity; OSpan = operation span; SymSpan = Symmetry Span; RotSpan = rotation span; PM = number of targets identified precondition; LDT.F = accuracy to prospective memory targets in the focal lexical decision prospective memory condition; Odd/Even.F = accuracy to prospective memory targets in the focal odd-even judgment task; Symm.F = accuracy to prospective memory targets on the focal symmetry judgment task; LDT.NF = accuracy to prospective memory targets in the non-focal lexical decision prospective memory condition; Odd/Even.NF = accuracy to prospective memory targets in the non-focal odd-even judgment task; Symmetry = accuracy to prospective memory targets on the non-focal symmetry judgment task. Gf = fluid intelligence; RAPM = Ravens progressive matrices; LetterSet = Letter set task; NumSeries = number series task; AC = attention control; VisArrays = visual arrays; ASaccade = anti-saccade.

Subsequent to the identification of a single prospective memory factor, a second CFA was run with all tasks loading onto a single factor. This is the CFA for which the following structural equation models will be based.

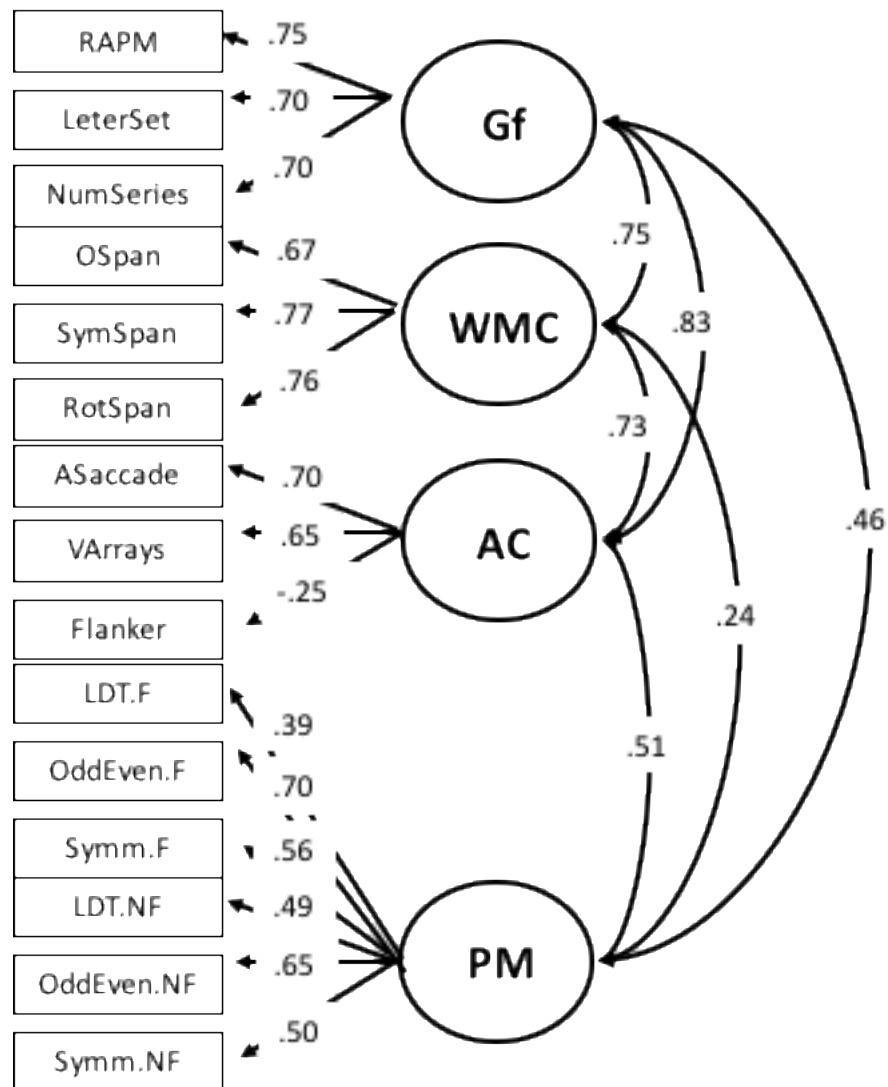


Figure 11. CFA with a single prospective memory latent factor. Model fit was good. Chi sq=128.41 (80) ; $P < .05$; CFI = .96 RMSEA = .04. Working memory capacity, fluid intelligence, and attention control were all highly correlated as anticipated. The highest correlation to prospective memory was attention control with fluid intelligence also very close.

The CFA for the following models using a single prospective memory factor is presented in figure 11. This model also showed good fit. In the interest of thorough theoretical evaluation all models to be presented were run with independent focal and non-focal latent factors as well. However, all models showed the same pattern of relationship between cognitive factors and prospective memory performance independent of whether the latent variable was a single prospective memory factor including all tasks, a non-focal only-factor, or a focal-only factor. Additional analyses which consist of only a singular focal or non-focal prospective memory latent factor are located in the Appendix section of this document.

Working Memory Capacity and Prospective Memory Performance

My first question regarding cognition and performance was whether or not working memory capacity measures predict prospective memory performance at the latent level. In order to test this, a single path model was constructed from our working memory capacity factor to our single prospective memory factor.

As Figure 12 shows, there was a significant relationship between working memory capacity and prospective memory performance. In structural equation models the amount of variance accounted for at the latent level is half of the path value. This means that working memory capacity accounts for 5.3% of the variance in prospective memory performance. Moreover, this variance is significantly different from zero. Although theories and studies have emphasized the potential for working memory capacity to show a strong relationship to prospective memory performance, this model suggests that while there is a significant relationship, the amount of variance in performance accounted for by working memory capacity is relatively low. However, this

factor accounted for a small percentage of the variance in performance. Next, I tested whether or not fluid intelligence also predicted prospective memory performance at the latent level.

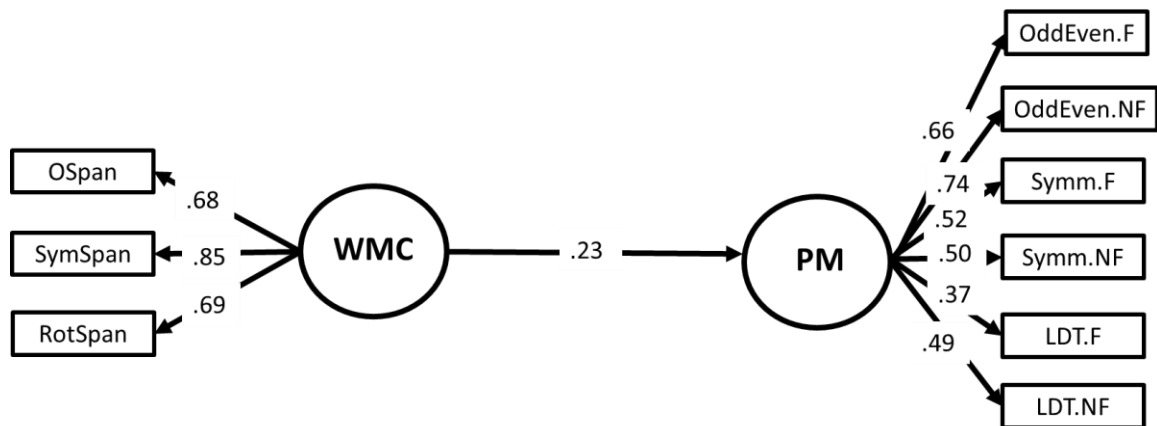


Figure 12. WMC predicting a single PM latent factor. Model fit was good Chi sq=58.34 (26); $p < .05$; CFI=.96; RMSEA = .06. The path from working memory capacity to prospective memory performance was significant, and accounted for 5.3% of the variance in prospective memory performance. Note for all figures abbreviations are as follows: WMC = working memory capacity; OSpan=operation span; SymSpan=Symmetry Span; RotSpan= rotation span; PM = number of targets identified precondition; LDT.F= accuracy to prospective memory targets in the focal lexical decision prospective memory condition; OddEven.F = accuracy to prospective memory targets in the focal odd-even judgment task; Symm.F = accuracy to prospective memory targets on the focal symmetry judgment task; LDT.NF= accuracy to prospective memory targets in the non-focal lexical decision prospective memory condition; OddEven.NF = accuracy to prospective memory targets in the non-focal odd-even judgment task; Symm.NF = accuracy to prospective memory targets on the focal symmetry judgment task.

Fluid Intelligence and Prospective Memory Performance

Figure 13 shows the significant path from fluid intelligence to prospective memory performance. Moreover, fluid intelligence predicted 21.2% of the variance in prospective memory performance. This is twice as much variance in performance than was predicted by working memory capacity. So the answer to my first latent variable

analysis question is that yes, both working memory capacity and fluid intelligence predict prospective memory performance, but to differing degrees.

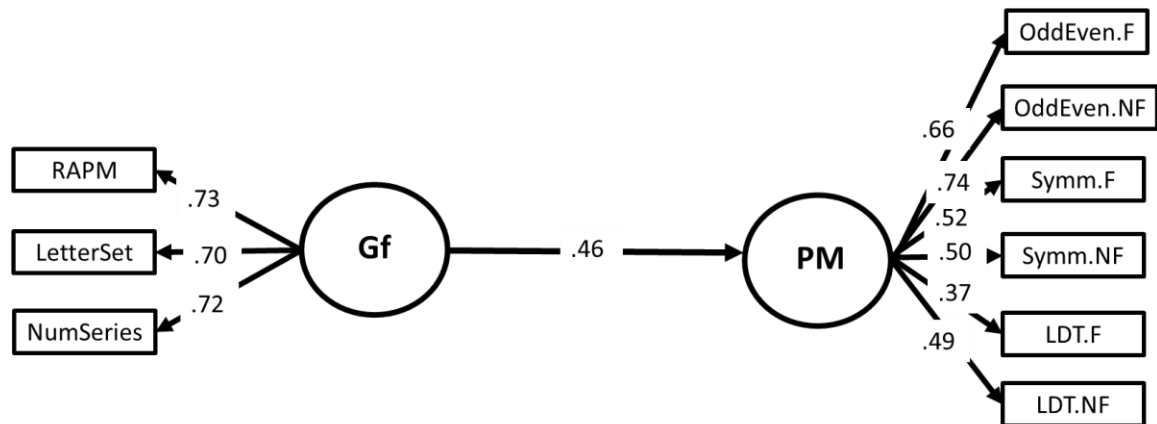


Figure 13. Gf predicting a single PM latent factor. Model fit was good Chi sq=60.69 (26); $p < .05$; CFI=.94; RMSEA = .07. The path from fluid intelligence to prospective memory performance was significant, with fluid intelligence accounting for 21.2% of the variance in prospective memory performance. Note abbreviations are as follows: Gf = fluid intelligence; Raven=Ravens progressive matrices; LetterSet=Letter set task; NumSeries= number series task; LDT.F= accuracy to prospective memory targets in the focal lexical decision prospective memory condition; OddEven.F = accuracy to prospective memory targets in the focal odd-even judgment task; Symm.F = accuracy to prospective memory targets on the focal symmetry judgment task; LDT.NF= accuracy to prospective memory targets in the non-focal lexical decision prospective memory condition; OddEven.NF = accuracy to prospective memory targets in the non-focal odd-even judgment task; Symm.NF = accuracy to prospective memory targets on the focal symmetry judgment task.

Fluid Intelligence and Working Memory Capacity

My second question was, when compared directly, does fluid intelligence predict performance beyond working memory capacity at the latent level? In other words, when both working memory capacity and fluid intelligence are allowed to correlate in a model, do they both show independent predictive validity? If both paths are significant, then both working memory capacity and fluid intelligence predict unique variance in prospective memory performance. However, if only one path is significant, then no additional predictive variance is accounted for by the other factor. I predicted that fluid intelligence

would be the dominating factor, as the ability to reduce outward interference from irrelevant stimuli would be advantageous in maintaining the prospective memory intention active.

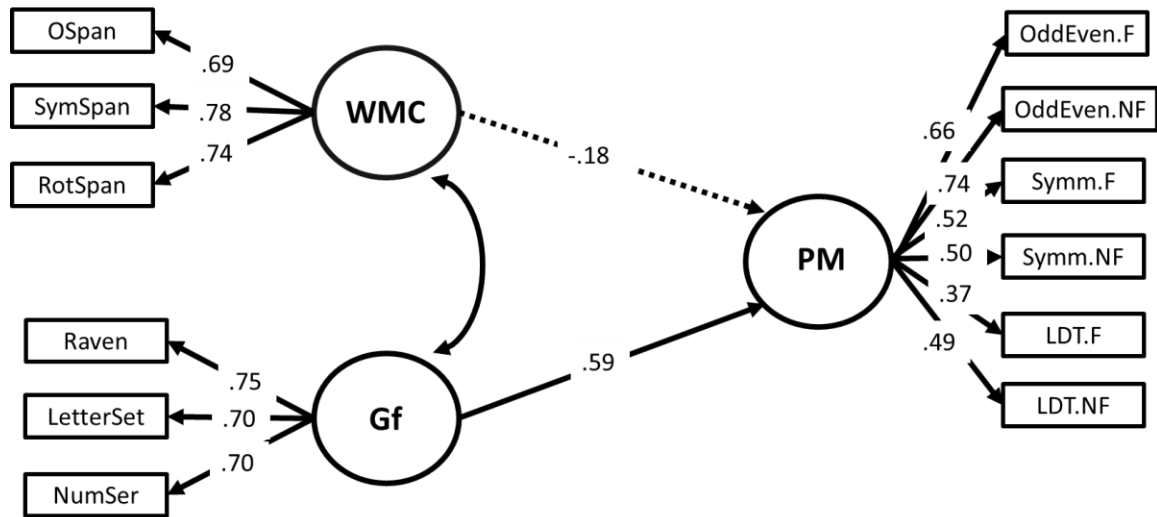


Figure 14. Contributions of WMC and Gf to PM. Model fit was good Chi sq=98.45 (51); $p < .05$; CFI=.95; RMSEA = .06. Only the path from fluid intelligence to prospective memory performance was significant. This path accounted for almost 34.8% of the variance in prospective memory performance.

As figure 14 shows, when both fluid intelligence and working memory capacity are allowed to correlate in a model, only fluid intelligence predicted performance on the prospective memory factor. This indicates that there is no significant relationship between working memory capacity and prospective memory performance beyond that which is captured by measures of fluid intelligence, which account for 34.8% of the variance in prospective memory performance.

Maintenance and Disengagement in Prospective Memory Performance.

Next, I tested the idea that aspects of maintaining information active, as well as releasing no-longer relevant information, may both be beneficial processes for

prospective memory performance. In order to evaluate this distinction, the same model used by Martin and colleagues (submitted) was run. In this model, a common maintenance factor was created by cross loading all of the working memory and fluid intelligence measures onto on a single common ‘maintenance’ factor. The cross loading of tasks onto a single factor pulls all of the shared variance between the tasks into that factor. The second factor, now reflects only residual variance from the fluid intelligence factor which is not common to the maintenance oriented working memory tasks. This second factor, which now only reflects residual variance from the fluid intelligence measures, is primarily disengagement oriented based on the framework proposed by Shipstead, Harrison, and Engle (2016).

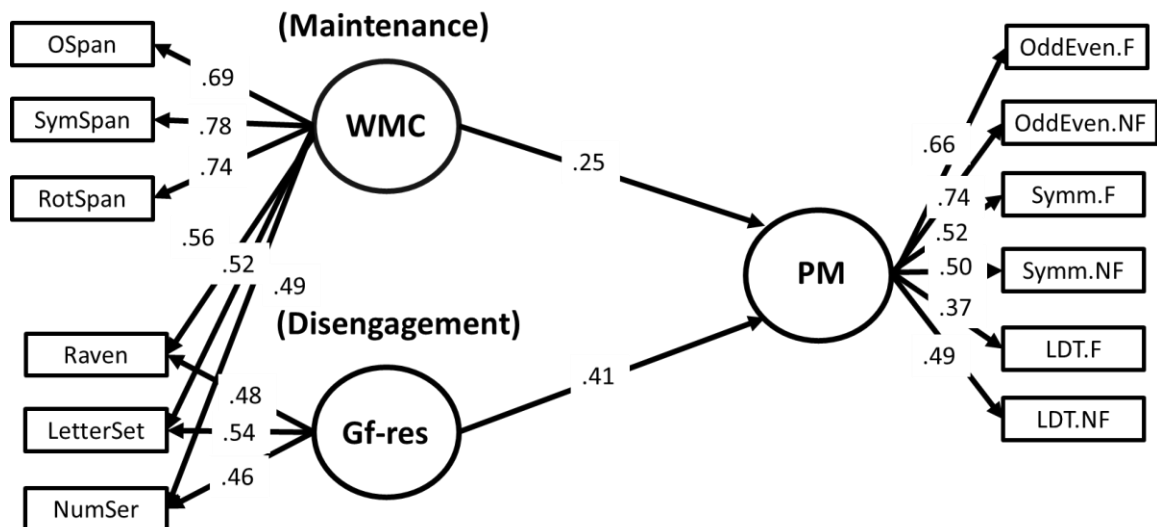


Figure 15. Contributions of maintenance and disengagement to PM. Model fit was good Chi sq=97.11 (49); $p < .05$; CFI=.95; RMSEA = .06. Both paths were significant with maintenance related variance accounting for 6.3% of the variance in prospective memory performance. Disengagement related variance accounted for 16.8% of the variance in prospective memory performance.

In figure 15 both the path from the common ‘maintenance’ factor, and the residual ‘disengagement’ factor were significant. This result indicates that both maintenance and disengagement processes are important for successful prospective memory performance. Further, both predicted unique variance in performance. Interestingly, the residual variance of fluid intelligence not shared with the complex span measures still predicted more variance in performance than did a common factor which includes the complex span measures. This result suggests that releasing no-longer relevant information is even more beneficial to performance than the active maintenance of information, or in this case the prospective memory intention.

Attention Control Mediation

Before presenting the results for this section, I would first like to remind readers of the measures of attention control used for this study. They are as follows:

- 1) The antisaccade task, in which participants were presented with a fixation followed by a flashing asterisk at the side of the screen. The participant then identified whether a letter presented on the opposite side from the flash was a Q or an O (this target is presented briefly and then masked). The dependent measure was the number of trials correctly identified.
- 2) The visual arrays task. Participants were presented a color, red or blue, followed by a series of red and blue rectangles at various angles around the screen presented very briefly. Participants had to identify whether the orientation of a

block (in the cued color) has changed orientation from the first screen. The dependent measure was a k score.

- 3) The Erickson flanker. Participants saw a series of 5 arrows. They had to identify whether the arrow in the center was congruent with or incongruent with the other arrows in the series. The dependent measure was a reaction time difference score between congruent and incongruent trials.

I reiterate the nature of these tasks to emphasize the fact that they are inherently different from both the working memory, fluid intelligence, and prospective memory tasks used in this study. All of the attention control measures are also very simple from a task design perspective.

My final latent factor question was, does attention control mediate the relationship between working memory capacity and/or fluid intelligence, and prospective memory performance? In theory, both of the aspects of maintenance and disengagement fall under control of the central executive. Subsequently, the degree to which attention control reflects the functions of the central executive, should account for the variance predicted by both working memory capacity and fluid intelligence. Two final mediation models were run, one for working memory capacity, and one for fluid intelligence. If no independent contributions of working memory capacity and fluid intelligence are observed beyond attention control, then, attention control is the driving force behind the performance. If, however, there are significant predictive paths from working memory capacity or fluid intelligence in addition to attention control, then either attention control is not adequate to reflect the relevant processes of the central executive related to these

higher order abilities, or there is variance captured by working memory capacity and fluid intelligence that is predictive of performance beyond attention control.

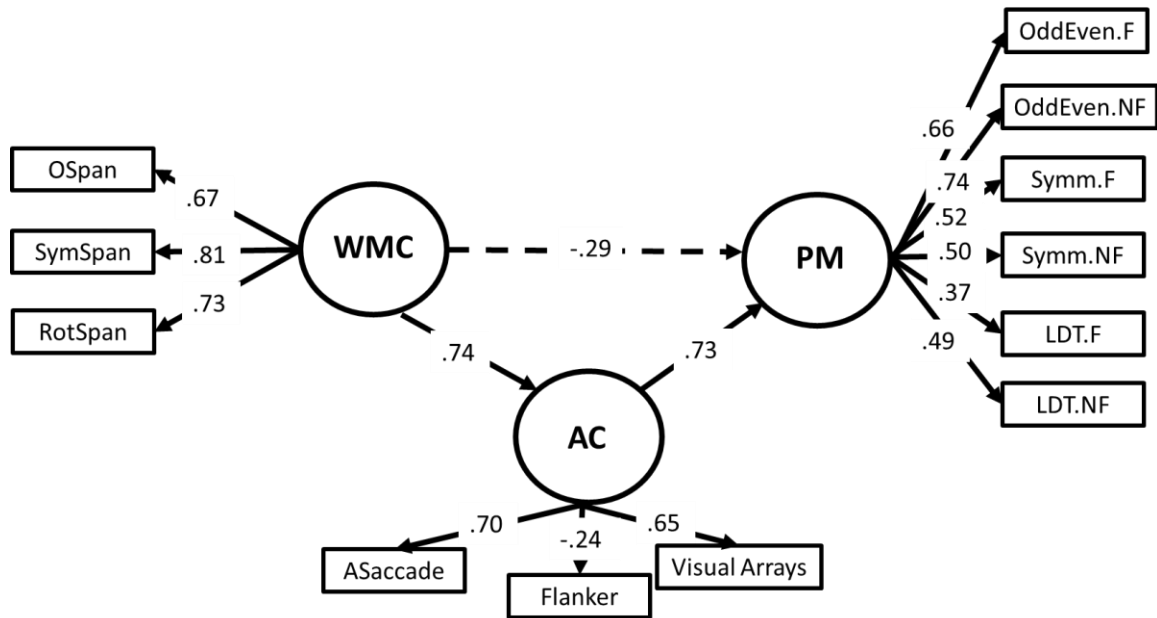


Figure 16. Mediation analysis between WMC and PM. Model fit was good Chi sq=85.82 (51); $p < .05$; CFI=.95; RMSEA = .05. Paths from working memory capacity to attention control, and attention control to prospective memory performance were significant. The path from fluid intelligence to prospective memory performance was not significant.

Figure 16 shows the attention control mediation analysis for working memory capacity. The purpose of this model was to see if working memory capacity still predicts prospective memory performance beyond the variance it shares with attention control. The lack of a significant path from working memory capacity to prospective memory performance, after attention control was included as a mediating variable, showed that the predictive power of working memory capacity demonstrated by previous models was due to the role of attention control. Further, although the residual between working memory capacity and prospective memory is not significant, it is still fairly high, and negative,

this is most likely due to high levels of multicollinearity between factors which can sometimes result in spurious but typically non-significant relationships.

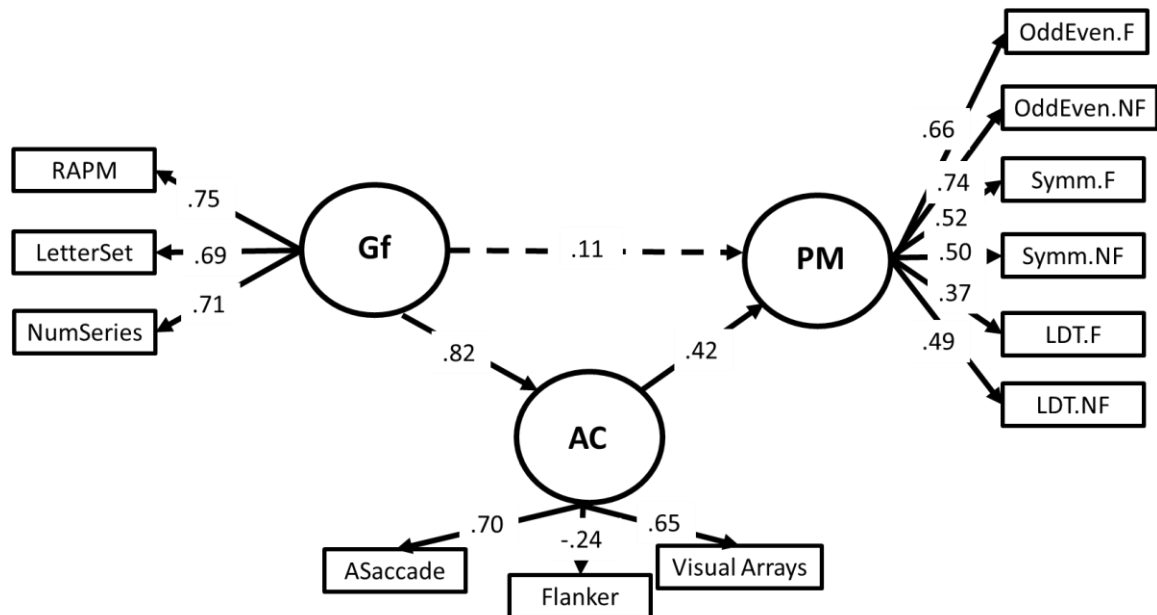


Figure 17. Mediation analysis between Gf and PM. Model fit was good Chi sq=84.69 (51); $p < .05$; CFI=.96; RMSEA = .05. Paths from fluid intelligence to attention control, and attention control to prospective memory performance were significant. The path from fluid intelligence to prospective memory performance was not significant.

Figure 17 shows the attention control mediation analysis for fluid intelligence.

The purpose of this model was to see if fluid intelligence still predicted prospective memory performance beyond the variance it shares with attention control. The lack of a significant path from fluid intelligence to prospective memory performance, after attention control was included as a mediating variable, showed that the predictive power of fluid intelligence demonstrated by previous models was due to the role of attention control. Although not all of the variance in fluid intelligence was captured by attention control in predicting prospective memory performance (as was the case with working memory capacity) there is still no additional predictive value of fluid intelligence.

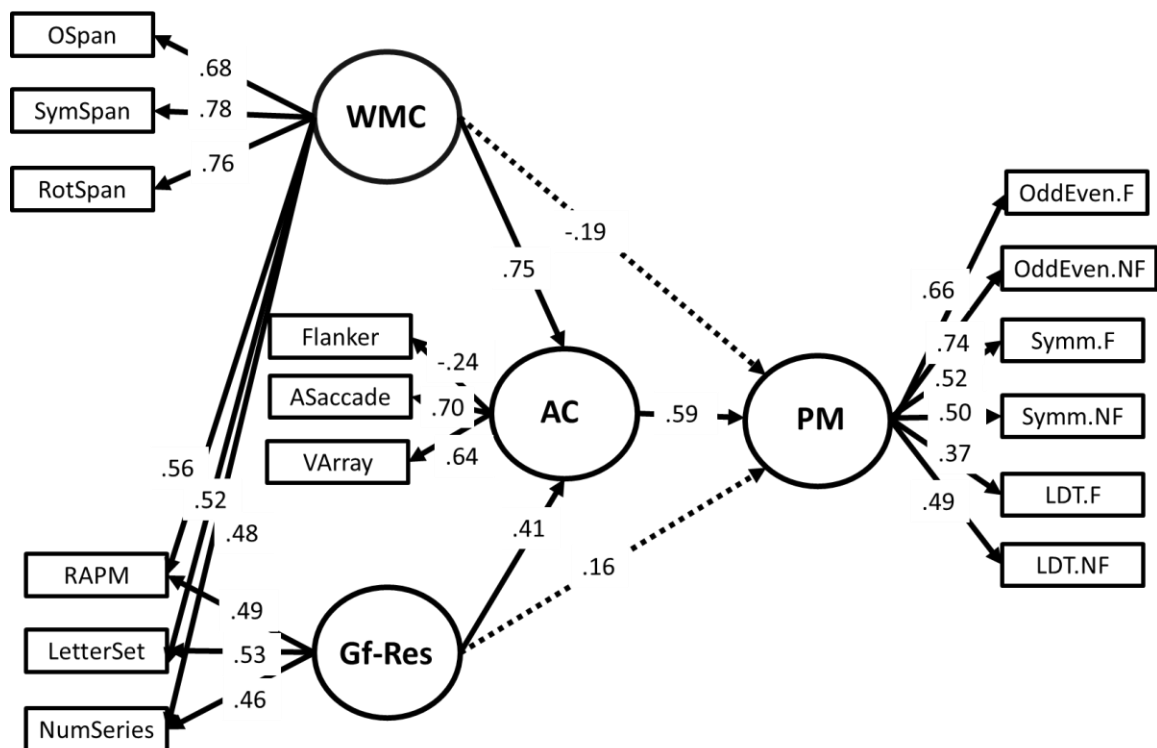


Figure 18. Mediation analysis between maintenance and disengagement. Model fit was good. Chi sq= 143.72 (78) $P < .05$; CFI=.95; RMSEA=.05. The paths from maintenance and disengagement to attention control were both significant. The path from attention control to prospective memory performance was the only significant predictor of performance (accounting for 34.8% of the variance in prospective memory performance).

Figure 18 tested the attention control mediation in the context of viewing working memory capacity and fluid intelligence as reflecting processes of maintenance and disengagement. Specifically, if the functions of the central executive which govern maintenance and disengagement are sufficiently captured by attention control, then there should be no residual variance reflected by either of these constructs beyond attention control. The paths between maintenance, disengagement, and attention control were all significant. As with all previous models, attention control fully mediated all variance in the model, and was the only significant factor predicting prospective memory

performance (predicting 34.8% of the variance in performance, and being most strongly related to working memory capacity).

One final post-hoc model was run related to figure 18 above. Specifically, we had developed and deployed several new attention control measures in an attempt to create a more robust measure of attention control. Specifically, these measures were designed to not rely on reaction time difference scores. In all of the models presented thus far, the lowest task to factor correlation is between the flanker and the attention control factor. This factor remained robust due to the strength of the antisaccade and visual arrays tasks. However, I wanted to see if more variance would be accounted for given a factor with a stronger attention control loading. To this end I substituted performance on the traditional Erickson flanker, with that of performance on a modified version in which the response deadline was adaptive. In this task, participants still reported whether a center arrow was point in the same (congruent) or opposite (incongruent) direction as the other arrows. However, the response deadline for all participants was stair-stepped up and down based on their accuracy on 15 out of 18 trials per block, over a series of 18 blocks. Participants' final score was their response deadline at the end of the 18th block (See Appendix C for a full task description). This allowed for a third measure of attention control which did not relay on reaction time difference scores, but was otherwise not fundamentally different in structure from the traditional Erickson flanker. As the model I will present shows, it shows a much stronger relationship to the attention control factor than the traditional factor. Further, this addition increased the amount of variance in prospective memory performance predicted by the attention control factor.

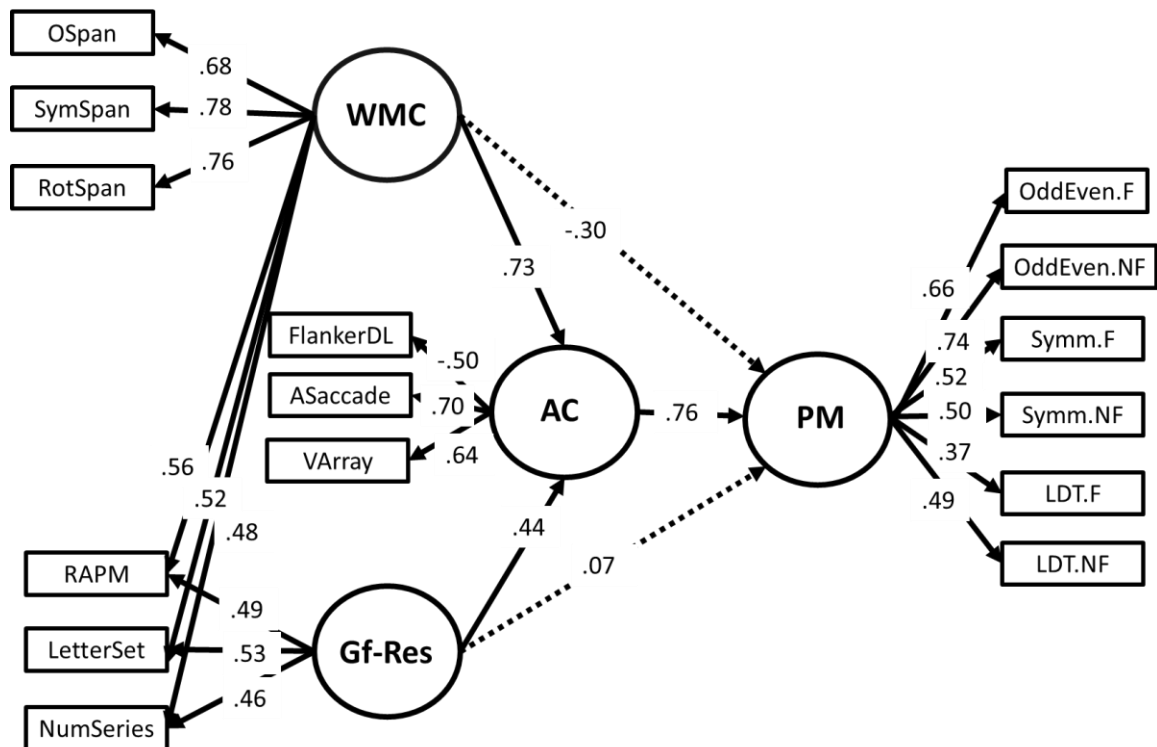


Figure 19. Maintenance and disengagement mediation analysis with flanker deadline task substitution. Model fit was good. Chi sq= 143.72 (78) $P < .05$; CFI=.95; RMSEA=.05. The paths from maintenance and disengagement to attention control were both significant. The path from attention control to prospective memory performance was the only significant predictor of performance. The path was also higher than in the previous model using the traditional flanker, meaning more prospective memory performance variance is captured when a more cohesive measure of attention control is used.

Figure 19 shows the same pattern of results as figure 18. The paths between maintenance, disengagement, and attention control were all significant, and essentially unchanged from figure 18. However, when the deadline flanker was loaded onto attention control, the new attention control factor now accounted for 57.8% of the variance in prospective memory performance. This is a substantial increase from the 34.8% of variance in prospective memory performance accounted for by the attention control factor using the traditional flanker. In other words, changing one task to one with a higher reliability resulted in an 23% increase in predicted variance.

The overall conclusion based on these models suggests that the primary factor of importance in terms of prospective memory performance is attention control. Moreover, the way in which attention control is measured has a substantial bearing on how well it predicts performance across a wide range of abilities.

Ongoing Task Performance

Ongoing task performance descriptive statistics are presented by task. For all tasks, participants' ongoing task accuracy as well as mean reaction time for the ongoing task are presented by condition (baseline, focal, and non-focal). Mean reaction time data was trimmed for accuracy. A second series of analyses compared mean reaction time not trimmed on accuracy and found no differences between the two data sets. Subsequently, only data trimmed for accuracy is presented. Correlational analyses were only completed on subjects who had all three prospective memory tasks, no imputations were used for the following analyses.

Table 4a-c. Ongoing task performance statistics divided by prospective memory task condition.

Descriptive Statistics: Lexical Decision

	N	Minimum	Maximum	Mean	Std. Deviation
LDTBaseline.Task.ACC	304	.51	1.00	.9243	.08549
LDTFocal.Task.ACC	302	.46	1.00	.8982	.10390
LDTNF.Task.ACC	304	.49	1.00	.9011	.10043
LDTBaseline.Task.RT	304	375.40	5495.17	840.2120	360.45874
LDTFocal.Task.RT	302	261.63	4192.81	867.6836	350.15713
LDTNF.Task.RT	304	308.52	5524.21	874.1187	362.40539

Descriptive Statistics: Odd-Even

	N	Minimum	Maximum	Mean	Std. Deviation
OEBaseline.Task.ACC	265	.39	1.00	.9387	.07799
OEFocal.Task.ACC	265	.41	.97	.8844	.09627
OENF.Task.ACC	265	.43	.97	.8846	.09776
OEBaseline.Task.RT	265	385.60	2669.87	702.2491	235.86658
OEFocal.Task.RT	265	226.52	1943.18	747.7394	234.24934
OENF.Task.RT	265	227.27	1562.73	724.9806	202.95497

Descriptive Statistics: Symmetry

	N	Minimum	Maximum	Mean	Std. Deviation
SymmBaseline.Task.ACC	265	.43	.99	.9310	.06974
SymmFocal.Task.ACC	265	.45	1.00	.9140	.10060
SymmNF.Task.ACC	265	.36	.99	.8657	.13074
SymmBaseline.Task.RT	265	185.95	3330.51	1142.6122	550.00154
SymmFocal.Task.RT	265	253.10	2994.60	988.2546	444.03840
SymmNF.Task.RT	265	192.10	3324.48	1032.7314	427.06004

Note. Reaction time data is presented based on accurate trials only.

No significant reaction time differences were observed between the baseline and focal or baseline and non-focal lexical decision trials. A significant difference in reaction time was observed between the baseline ($M = 702.25$) and focal odd even task ($M = 747.74$). $t = -2.675$; $p < .05$. Reaction times were significantly different between the baseline ($M = 1142.61$) and focal conditions ($M = 988.25$) in the symmetry judgment task $t = 7.175$, $p < .05$. Reaction times were also significantly different between the baseline ($M = 1142.61$) and non-focal conditions ($M = 1032.73$) in the symmetry judgment task $t = 5.523$, $p < .05$. However, both of these differences reflect a decrease in reaction time from baseline, rather than an increase. Alternately, there was a significant difference in reaction time between the focal and non-focal symmetry judgment conditions, such that reaction time was slower on average in the non-focal (10.32.73) condition than in the focal condition (988.25) $t = -2.89$, $p < .05$.

Table 5. Summary table for all ongoing task accuracy costs.
Paired Samples Test Summary Table for Task Accuracy

Paired Differences									
		95% Confidence Interval of the Difference					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	LDTBaseline.Task.ACC - LDTFocal.Task.ACC	.02566	.07144	.00411	.01757	.03375	6.241	264	.000
Pair 2	LDTBaseline.Task.ACC - LDTNF.Task.ACC	.02320	.05792	.00332	.01666	.02973	6.983	264	.000
Pair 3	LDTFocal.Task.ACC - LDTNF.Task.ACC	-.00250	.05774	.00332	-.00903	.00404	-.751	264	.453
Pair 4	OEBaseline.Task.ACC - OEFocal.Task.ACC	.05435	.07164	.00493	.04463	.06407	11.020	264	.000
Pair 5	OEBaseline.Task.ACC - OENF.ACC	.05410	.07407	.00510	.04405	.06415	10.610	264	.000
Pair 6	OEFocal.Task.ACC - OENF.Task.ACC	-.00025	.06141	.00423	-.00859	.00808	-.060	264	.953
Pair 7	SymmBaseline.Task.ACC - SymmFocal.Task.ACC	.01701	.07242	.00483	.00749	.02652	3.522	264	.001
Pair 8	SymmBaseline.Task.ACC - SymmNF.Task.ACC	.06529	.11264	.00751	.05049	.08009	8.695	264	.000
Pair 9	SymmFocal.Task.ACC - SymmNF.Task.ACC	.04829	.10245	.00683	.03483	.06174	7.070	264	.000

A summary of the pairwise t-test results conducted for ongoing task accuracy is presented above. All tasks showed significantly lower accuracy from the baseline to the focal, and the baseline to non-focal. Only the symmetry judgment also showed an additional change in ongoing task accuracy from the focal condition to the non-focal condition such that participants were also less accurate in the non-focal as compared to the focal condition. Small significant correlations (.157 and .139) between the Ravens and the focal and non-focal symmetry judgment monitoring scores were found. No other correlations were significant. No correlations between monitoring costs and prospective memory performance within the same condition were significant.

Next, bin scores measuring speed-accuracy tradeoff changes were calculated for each participant.

Table 6. Descriptive statistics showing speed and accuracy tradeoff made between baseline and focal, and baseline and non-focal conditions of each task.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
OEFocalBinScore	265	180.00	5780.00	711.3913	665.02439
OENFGGrandBinScore	265	714.00	5442.00	2295.2957	506.45206
LDTFocalBinScore	265	953.00	6157.00	2743.6222	1112.78241
LDTNFBinScore	265	1073.00	6137.00	2692.0056	1113.74909
SymmFocalBinScore	265	200.00	4454.00	1559.7585	733.34224
SymmNFBinScore	265	577.00	6546.00	2339.1014	1009.47683

Table 7. Pairwise significance tests for all bin scores.
BinScore Paired Samples Test Summary Table

		Paired Differences						Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error	95% Confidence Interval of the Difference		df	
					Lower	Upper		
Pair 1	OEFOcalBinScore - OENFBinScore	-1554.1321	537.62956	33.02632	-1619.1606	-1489.1036	264	.000
Pair 2	LDTFocalBinScore - LDTNFBinScore	50.42180	280.01045	19.27671	12.42114	88.42247	264	.010
Pair 3	SymmFocalBinScore - SymmNFBinScore	-789.08491	828.04363	56.87027	-901.19160	-676.97821	264	.000

All changes in bin scores from the focal to the non-focal condition were significant (see tables 6 and 7). In the odd even task and the symmetry judgment task, participants showed an increase in their speed accuracy trade off in the non-focal condition relative to the focal condition. However, in the lexical decision task, they were higher in the focal condition than the non-focal condition. This is likely due to the high standard deviation in this condition relative to others, as initial analyses with a smaller sample revealed a similar pattern to that of the other two task conditions.

Table 8. Correlations between bin scores and the highest loading task for each latent cognitive factor.

Bin Score Correlations

	OEFOcalBinScore	OENFBinScore	LDTNFBinScore	LDTFocalBinScore	SymmNFBinScore	SymmFocalBinScore
RAPM	-.257	-.131	.141	.162	.058	.367
ASaccade	-.277	-.070	.018	.040	-.035	.293

Note. Significant correlations are in bold.

Additionally, correlational analyses were conducted with the bin scores for each task. Bin scores were positively correlated with ability in the symmetry judgment task, and negatively correlated with ability in the odd even task. In other words, higher ability individuals were able to recognize the increased difficulty of the task in a more demanding situation, whereas higher ability individuals did not under a less demanding task condition. Bin scores within task were negatively correlated with performance in the odd-even judgment task (-.394 and -.2). No other within task bin scores and prospective memory performance were correlated.

The only post hoc latent variable analysis which resulted in acceptable model fit is presented below.

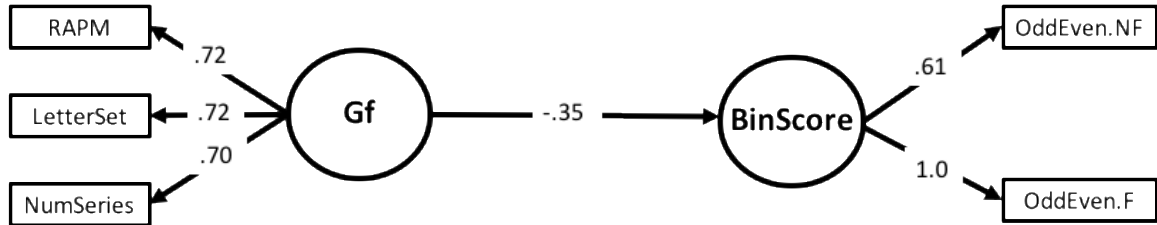


Figure 20. Gf predicting odd-even PM task bin scores. Model fit was good Chi sq=56.4 (21); $p < .05$; CFI=.95; RMSEA = .05. The path from fluid intelligence to bin scores a significant and accounted for 12.3% of the variance in these measures.

Figure 20 shows a post-hoc analysis with bin scores (speed accuracy trade off adjustments) from the odd-even judgment task. As figure 13 shows, fluid intelligence, but not working memory capacity was negative related to speed and accuracy adjustments. That is to say, higher ability individuals made fewer adjustments to their speed and accuracy in general when prospective memory demands were added, than did lower ability individuals. As with the prospective memory intention data, however, this relationship was also mediated by attention control.

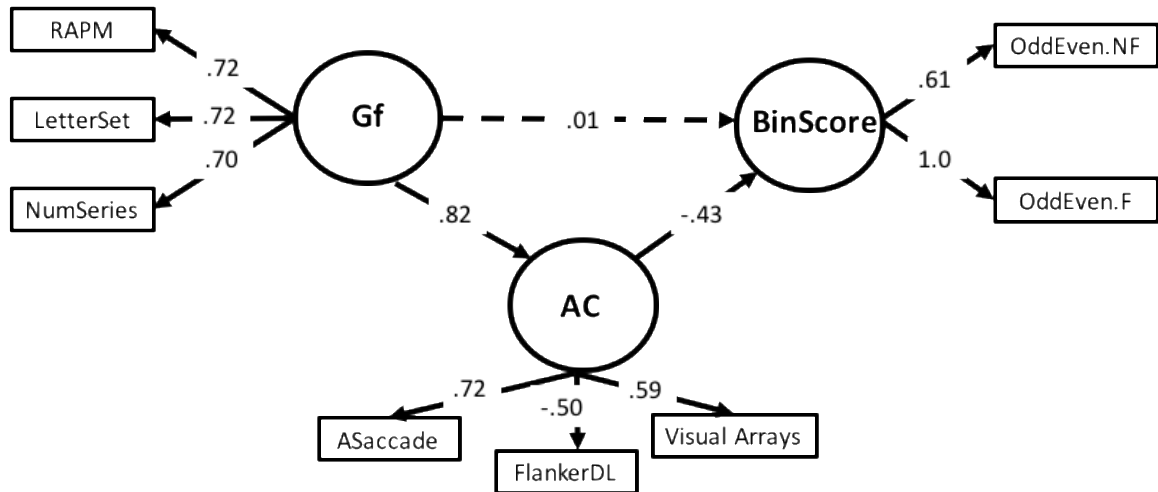


Figure 21. Mediation analysis between Gf and odd-even PM task bin scores. Model fit was good Chi sq=86.5 (51); $p < .05$; CFI=.95; RMSEA = .05. The only significant predictor of bin scores was attention control.

The mediation analyses conducted for the bin scores is presented in figure 21.

This analysis showed that the relationship between fluid intelligence and adjustments to ongoing task performance were fully mediated by attention control. Once attention control was added the fluid intelligence model presented in figure 19, the path from fluid intelligence to ongoing task adjustments was no longer significant. To the degree that ability is related to ongoing task performance, it also appears to be rooted in the ability to control attention.

CHAPTER 4

DISCUSSION

Prospective memory performance is an essential function of everyday life, and in some instances the ability to remember to perform an action in the future is a matter of life or death. However, we still lack a substantial amount of understanding regarding how prospective memory performance differs between individuals of varying cognitive ability. We have gained a significant amount of evidence regarding the impact of task manipulations on performance through the use of the laboratory paradigm; however, our understanding of the exact cognitive mechanisms underlying performance is still not well established. Moreover, the degree to which differences in these abilities are reflected in performance is a very young area of research.

Previous studies that have included regression or structural equation modeling still failed to present the prospective memory factor as a latent construct with predictors from multiple tasks, and even fewer incorporated both focal and non-focal factors. Further, this is the first time, to the author's knowledge that measures of fluid intelligence as well as attention control have been included to refine our understanding of performance at the latent level.

Results of this study answered the following questions:

- 1) Is prospective memory capacity a unitary factor at the latent level when a variety of tasks are used?

- 2) Do the relationships between working memory capacity and fluid intelligence and prospective memory performance differ when prospective memory tasks are focal or non-focal in nature?
- 3) Is the relationship between fluid intelligence and performance stronger than that of working memory capacity and performance?
- 4) Do the processes of maintenance and disengagement outlined by Shipstead, Harrison, and Engle (2016) independently predict prospective memory performance?
- 5) Does attention control mediate the relationship between these higher order ability constructs and performance?
- 6) Does the use of bin scores provide a more accurate description of ongoing task 'costs' across diverse task sets than the use of reaction time difference scores?
- 7) Are ongoing task costs, related to ability?

Overall, prospective memory performance in general was consistently higher in the focal conditions of the lexical decision task and the symmetry judgment task than in their respective non-focal conditions. However, a CFA suggested that at the latent level prospective memory was a unitary factor. Interestingly, the response rate to the prospective memory target was equivalent for both of the odd-even judgment task conditions. At first glance this appears as though both are equally demanding non-focal conditions; however, speed and accuracy data suggest that that non-focal condition was in fact more demanding. Specifically, participants showed an increase in their speed accuracy trade off in the non-focal condition compared to the focal (i.e. individuals were

slower and less accurate at performing the ongoing task in the non-focal condition than in the focal). Additionally, the more rapid response time and generally less demanding processing of the stimuli of the ongoing task may have resulted in difficulties relying on spontaneous retrieval mechanisms. In sum, participants showed more of an ongoing task cost that would reflect more effortful processing of the prospective memory intention under the non-focal condition than the focal in spite of a lack of overall differences in performance.

Using a series of structural equation modeling I found that both working memory capacity and fluid intelligence contribute significantly to prospective memory performance at the latent level. Further, there was no residual working memory capacity variance when the two were compared directly. Additionally, prospective memory performance reflected independent contributions of maintenance and disengagement as proposed by Shipstead, Harrison, and Engle (2016). Specifically, when a common factor was created that reflected maintenance and a second factor consisting of the disengagement related variance were compared, both paths were significant. This indicates that, although working memory capacity did not show an independent relationship to performance when compared to fluid intelligence, the maintenance related variance it largely reflects does independently predict performance on prospective memory tasks in addition to disengagement variance. Thus both actions of maintaining the intention, and or the task goals, as well as releasing no-longer relevant information result in higher prospective memory performance independent of task condition (focal vs non-focal). Further, although a single factor solution was presented above, models using

only a focal or non-focal prospective memory outcome variable also showed significant independent contributions of maintenance and disengagement processes (see appendices).

Finally, and most importantly, I conducted a series of mediation analyses with attention control. The aim of these analyses was to evaluate whether attention control fully or partially mediated the relationship between working memory capacity and prospective memory performance, as well as fluid intelligence and prospective memory performance. Fit for both models was ‘good’ and both models indicated that attention control fully mediated the relationship between working memory capacity and prospective memory performance, as well as the relationship between fluid intelligence and prospective memory performance. Further, full mediation through attention control continued to be the sole predictor of prospective memory performance when working memory capacity and fluid intelligence tasks were configured to reflect the processes of maintenance and disengagement.

The finding that attention control fully mediated the relationship between working memory capacity and fluid intelligence factors and the processes of maintenance and disengagement specifically has several major theoretical implications. First, the relationship between higher order cognitive processes such as working memory capacity and even fluid intelligence are secondary to differences in attention control when predicting prospective memory performance. Initially, I anticipated that fluid intelligence would be a better predictor of performance than working memory capacity. However, I was less certain that the relationship between fluid intelligence and performance could be explained in terms of attention control, which it was. Second, the lack of residual variance in the model reflecting the general processes of maintenance and disengagement

suggested that all performance relevant variance was reflected exclusively by my measure of attention control.

According to the theory of maintenance and disengagement proposed by Shipstead, Harrison, and Engle (2016), maintenance and disengagement are general processes which describe actions of the central executive. My results suggest that attention control is sufficient to explain the variance from these central executive processes as they relate to prospective memory performance. Further, the degree of prediction of the attention control factor is dependent on the tasks used to define and measure it. The simple change of one traditional measure of attention control, the Erickson flanker, to a version which did not rely on reaction time difference scores, resulted in a substantial increase in the predictive value of the attention control factor. Subsequently, the main factor of interest with regard to prospective memory performance is attention control. However, the degree to which it is able to predict performance, is dependent on how attention control is measured. The revised attention control factor presented in figure 12 suggests that studies using measures such as the traditional flanker or stroop, are likely under-estimating the degree to which attention control predicts differences in performance. Further, studies showing independent contributions of executive functions, based on these types of tasks which rely heavily on reaction time difference scores are likely reflecting task or error variance rather than meaningful differences in processing.

In summary, performance on focal and non-focal prospective memory tasks and the presumed underlying constructs are not as dissimilar as they might appear in experimentally driven theory when examined at the latent level. Specifically, the pattern

of relationships between cognitive factors and performance remained the same whether a single prospective memory factor was used, or independent focal and non-focal factors were used. Additionally, the overwhelmingly consistent indicator of performance was attention control and not working memory capacity or fluid intelligence.

My results suggest that inconsistent findings regarding the relationship between working memory capacity and prospective memory performance is likely due to the fact that working memory capacity plays a much smaller role in predicting prospective memory performance than does fluid intelligence. Moreover, both the relationship between working memory capacity and fluid intelligence are fully explained by differences in attention control, particularly when a robust factor is used. Subsequently, studies emphasizing cognitive ability through working memory capacity, may not find a consistent relationship as these tasks are ultimately reflecting less individual difference variance than measures of fluid intelligence or attention control measures. Additionally, many studies that do not conduct analyses at the latent level use a single indicator as a measure of ‘working memory capacity’. This is fundamentally flawed, as you can only extrapolate insofar as there are group differences on that specific task. Further, these studies often rely on the use of the operation span which is the lowest loading variable, and most problematic for identifying differences based on a cognitively diverse sample (see Draheim, Harrison, Embretson, & Engle (2017) for a review).

The ongoing task data was a bit less clear in its coherence across tasks. Overall the traditional stair step in reaction time as the task moved from focal to non-focal was not observed, in favor of a change in ongoing task accuracy. Once bin scores were calculated, they were generally more consistent across tasks, as well as related to ability

with higher fluid intelligence being reflected in less slowing and/or better accuracy as task demands increase. This pattern was not true for measures of ongoing task cost which solely relied on differences in reaction time. I believe this is due to the increased reliability of the bin scores compared to reaction time difference scores particularly when assessing group differences across a wide range of abilities. This is a similar issue as discussed above regarding the use of the traditional flanker in favor of one in which an adaptive, thresholding procedure is used.

The combined prospective memory accuracy data, latent level analyses, and ongoing task data present a challenge to the field. How do we define focal and non-focal prospective memory tasks at the latent level? Is this distinction valid when task demands and structure differ significantly? Although these tasks have been defined at experimental level by both the multi-process theory and dynamic multi-process theory in terms of degree of cue focality or target salience, these distinctions become irrelevant at the latent level when a wide range of abilities are considered. On the one hand, differences in prospective memory accuracy for the lexical decision task set as well as the symmetry judgment task set suggest that these conditions consist of focal and non-focal conditions, as do the ongoing task costs in the symmetry condition. However, no ongoing task costs were observed in the lexical decision condition that would indicate the more difficult non-focal task was in fact fundamentally different from the focal. In fact, the inverse relationship was shown with both reaction time data as well as bin scores suggesting that focal condition was actually more resource demanding. Additionally, the lack of a difference in prospective memory performance on the odd-even judgment task between the focal and non-focal condition would suggest that both conditions are equally resource

demanding. However, the difference in ongoing task costs measured in terms of a speed accuracy trade off show that the non-focal condition is in fact more demanding under these task conditions. Additionally, the fact that the speed-accuracy trade off relationship to ability was most pronounced in the odd even judgment task suggests that this measurement may be best employed when processing demands are low. Subsequently, the more rapid processing of stimuli may also account for the low prospective memory performance in the focal condition. In other words, participants have less time to engage spontaneous retrieval processes when they are processing very basic stimuli.

One additional potential explanation for the overall congruency in performance across all prospective memory conditions is the number of targets. Although four targets were chosen in order to have a sufficient range in performance for latent variable analyses, this frequency could have been generally monitoring inducing. This increase in monitoring would explain why there were differences between focal and baseline conditions, but not non-focal and baseline conditions. However, in spite of potential increases in monitoring in the focal condition, participants still made speed accuracy adjustments to a greater degree in the non-focal condition than in the focal conditions. In other words, the focality/salience distinction appears to function more in terms of degree of difficulty at the latent level, with more commonality across focal and non-focal task conditions than experimental studies would suggest.

In summary, I entered into this project assuming that fluid intelligence specifically and disengagement more generally, would be important for prospective memory performance under both focal and non-focal task conditions. Further, I anticipated observing a different pattern of results between cognitive ability and

prospective memory performance on focal and non-focal tasks. However, the analyses at the latent level, suggest that prospective memory performance, as measured with laboratory paradigms, is a singular construct at the latent level. These results are in contrast to findings by Rummel et al. (2017) which showed independent focal and non-focal factors. However, they did not employ a variety of types of focal and non-focal prospective memory tasks. Rather, focal and non-focal latent variables were created using a split half procedure of two independent tasks. While two factors can be imposed on the present analyses, the overall summary of the data suggest that making this distinction is theoretically irrelevant when examining underlying cognitive components of performance. One caveat I would make, however, regarding this conclusion is related to the number of targets in each task. It is possible that the number of targets resulted in more ongoing task adjustments in the focal condition than may typically be observed.

However, the number of targets does not fully explain why all of the tasks would load onto a factor in a well-fitting model in spite of their differences in performance across focal and non-focal conditions. Further, my results suggest that to the extent that ongoing task performance is related to ability across multiple types of tasks is contingent on more reliable measures of changes in ongoing task performance such as measures of speed and accuracy trade-offs. However, even these relationships are tenable at best given the poor model fit when evaluated at the latent level, and most consistently identified when the demands of the ongoing task are low and consistent across stimuli.

APPENDIX A

Models with a Single Non-Focal Prospective Memory Factor

Significant paths and loadings are identified by a single bold line, non-significant paths are identified by a dotted line.

Working Memory Capacity and Non-focal Prospective Memory Performance

My first question was whether or not working memory capacity measures predict non-focal prospective memory performance at the latent level. In order to test this a single path model was constructed from our working memory capacity factor to our non-focal prospective memory factor.

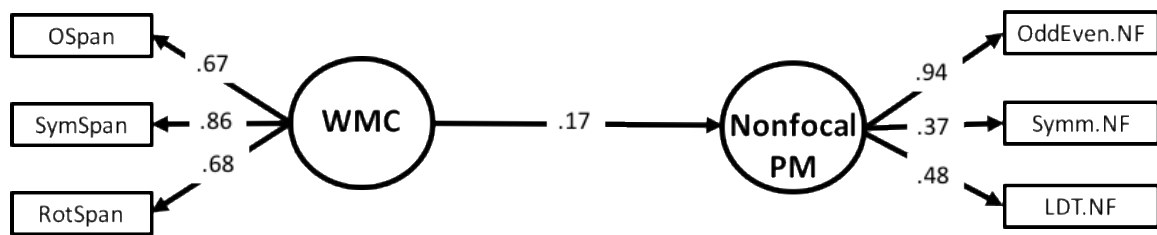


Figure A1. Working memory capacity predicting non-focal prospective memory latent factor. Model fit was good, and the chi-square value was not significant. Chi sq=9.09 (8); $p > .05$; CFI=1.0; RMSEA = .02. Note for all figures abbreviations are as follows: WMC = working memory capacity; OSpan=operation span; SymSpan=Symmetry Span; RotSpan= rotation span; Non-Focal PM = number of correctly responded to targets in the non-focal versions of all three tasks; LDT= lexical decision prospective memory condition; OddEven = odd-even judgment task; Symmetry = symmetry judgment task.

As Figure A1 shows, there was a significant relationship between working memory capacity and non-focal prospective memory performance. However, this factor accounted for a small percentage of the variance in performance (8.5%). Next I tested whether or not fluid intelligence also predicted non-focal prospective memory performance at the latent level.

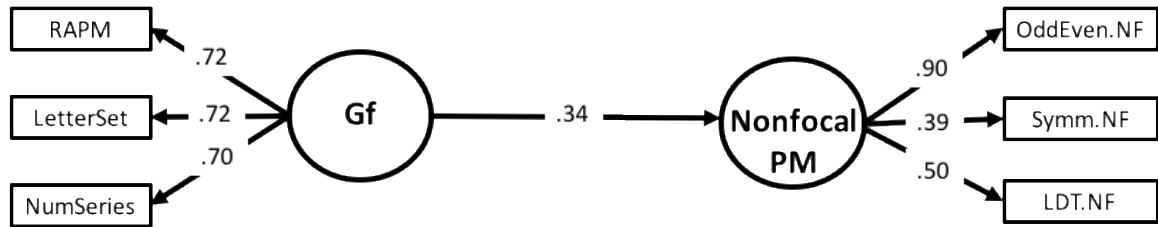


Figure A2. Fluid intelligence predicting non-focal prospective memory latent factor. Model fit was good and the chi-square value was not significant. Chi sq=4.04 (8); $p>.05$; CFI=1.0; RMSEA = .00. Note abbreviations are as follows: Gf = fluid intelligence; Raven=Ravens progressive matrices; LetterSet=Letter set task; NumSeries= number series task; Non-Focal PM = number of correctly responded to targets in the non-focal versions of all three tasks; LDT= lexical decision prospective memory condition; Odd/Even = odd-even judgment task; Symmetry = symmetry judgment task.

Figure A2 shows the significant path from fluid intelligence to non-focal prospective memory performance. Moreover, fluid intelligence predicted twice as much variance (17%) in prospective memory performance as working memory capacity (8.5%).

Fluid Intelligence vs. Working Memory Capacity

My second question was, when compared directly, does fluid intelligence predict performance beyond working memory capacity at the latent level? I believed this would be the case, as the ability to reduce outward interference from irrelevant stimuli would be advantageous in maintaining the prospective memory intention active.

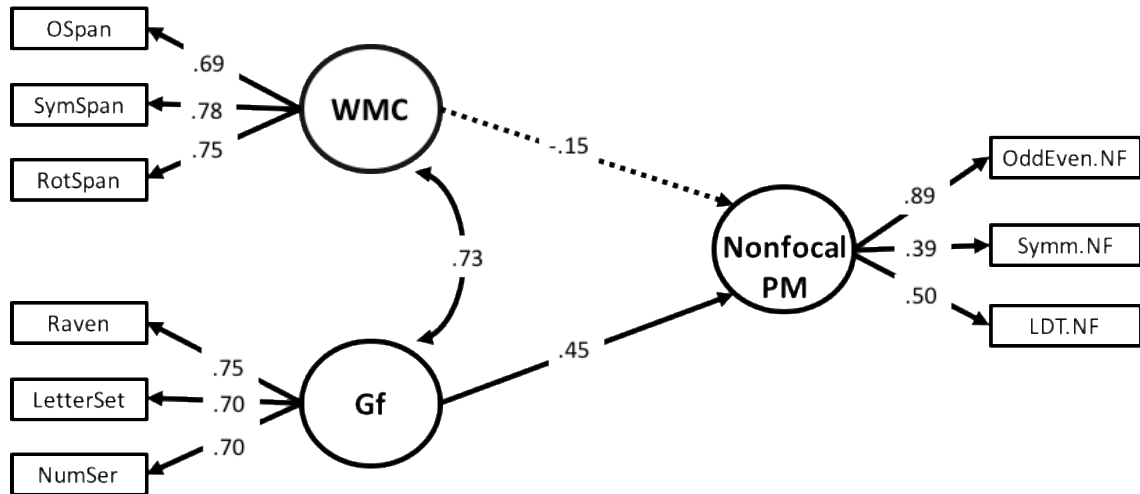


Figure A3. Contributions of working memory capacity and fluid intelligence to non-focal prospective memory performance. Note Model fit was good Chi sq=35.48 (22); $p < .05$; CFI=.98; RMSEA = .04. The only significant path is the path from fluid intelligence to non-focal prospective memory performance. Working memory capacity provides no additional predictive value beyond fluid intelligence which accounts for 22.5% of the variance in prospective memory performance.

As figure A3 shows, when compared directly, only fluid intelligence predicted performance on the non-focal prospective memory factor. Moreover, the path from working memory capacity to prospective memory performance was not different from zero.

Maintenance and Disengagement in Prospective Memory Performance.

Next, I tested the idea that aspects of maintaining information active, as well as releasing no-longer relevant information may both be beneficial processes for non-focal prospective memory performance. In order to evaluate this distinction, the same model used by Martin and colleagues (submitted) was run. In this model, a common maintenance factor was created by cross loading all of the working memory and fluid intelligence measures onto on a single common ‘maintenance’ factor. This second, which

now was residual variance from the fluid intelligence measures, in theory reflected disengagement.

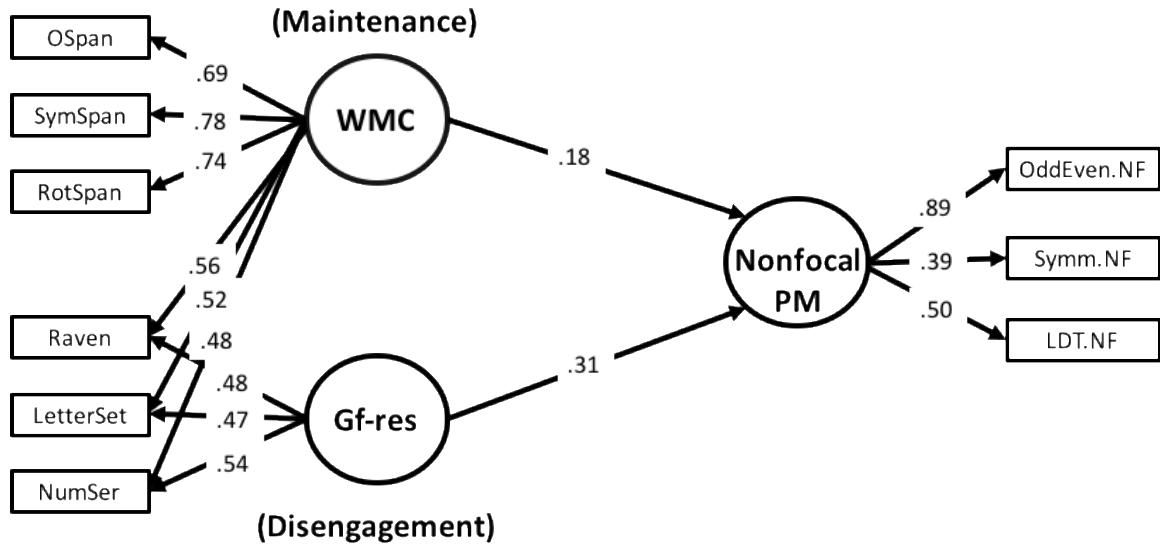


Figure A4. Contributions of maintenance and disengagement to non-focal prospective memory performance. Model fit was good $\chi^2=34.44$ (20); $p<.05$; CFI=.98; RMSEA = .04. Both the maintenance path and the disengagement significantly predict performance on the non-focal prospective memory factor. In total the two paths predict 24.5% of the variance in non-focal prospective memory tasks.

In figure A4 significant independent contributions from both ‘maintenance’ and ‘disengagement’ emerged, suggesting that both processes are important for predicting successful prospective memory performance under non-focal conditions. Together these paths accounted for 24.5% of the variance in prospective memory performance.

APPENDIX B

Models with a Single Focal Prospective Memory Factor

Significant paths and loadings are identified by a single bold line, non-significant paths are identified by a dotted line.

Focal prospective memory performance

The degree to which working memory capacity fluid intelligence relate to focal prospective memory performance was more exploratory; however, I anticipated that the degree to which fluid intelligence informs performance under focal conditions, would be through the use of disengagement, rather than maintenance. Moreover, any relationship between working memory capacity and performance would be due to its strong relationship to fluid intelligence.

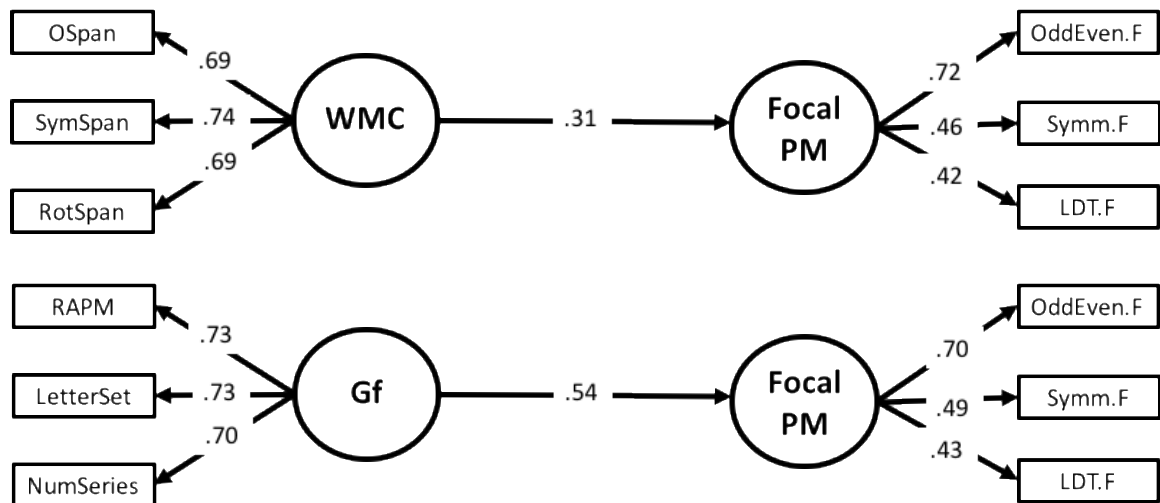


Figure B1. Working memory capacity and fluid intelligence independently predicting focal prospective memory performance. Model fit was good Model fit was good for working memory capacity, and the chi-square test was significant. Chi sq=11.99 (8); $p>.05$; CFI=.99; RMSEA = .04. Fluid intelligence model fit was good Chi sq=15.40 (8); $p<.05$; CFI=.97; RMSEA = .06. The path from working memory capacity was significant and predicted 15.5% of the variance in focal prospective memory performance. The path from fluid intelligence to prospective memory performance was also significant and accounted for 27% of the variance in prospective memory performance.

As figure B1 shows, both working memory capacity and fluid intelligence contributed significantly to focal prospective memory performance at the latent level. Working memory capacity accounted for 15.5% of the variance in performance, and fluid intelligence accounted for 27% of the variance in performance.

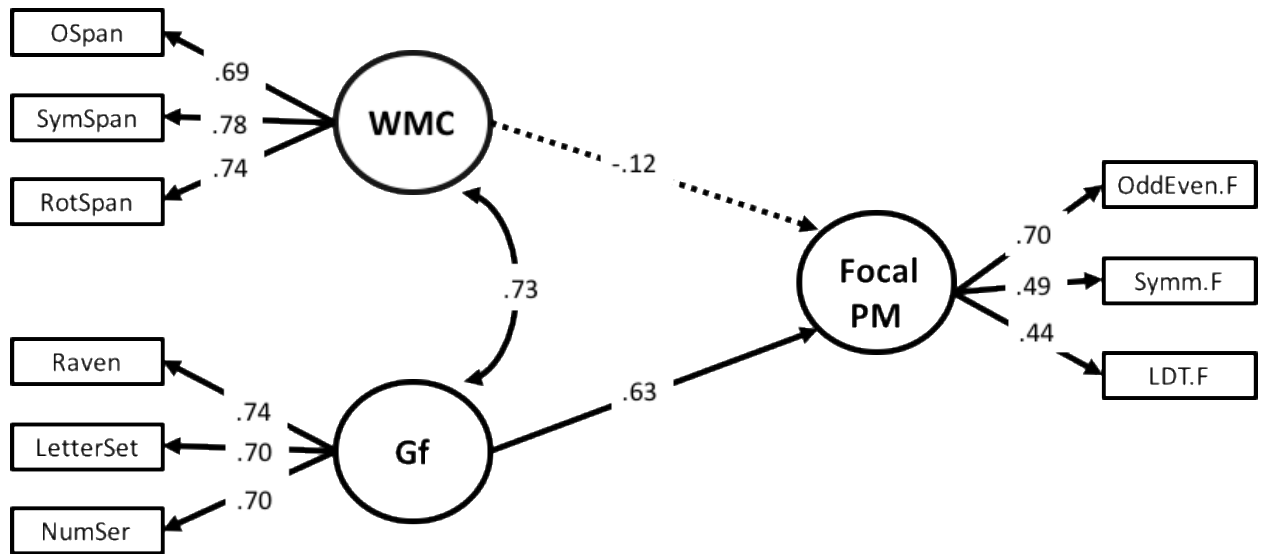


Figure B2. Contributions of working memory capacity and fluid intelligence to focal prospective memory performance. Model fit was good Chi sq=44.20.4 (22); $p < .05$; CFI=.97; RMSEA = .06. Only the path from fluid intelligence to prospective memory performance was significant (accounting for 31.5%) of the variance in performance.

Further in figure B2, once working memory capacity and fluid intelligence were compared directly, only the fluid intelligence path was significant (accounting for 31.5% of the variance in performance), but the path from working memory capacity to focal prospective memory performance was not. These results mirrored those of the non-focal condition.

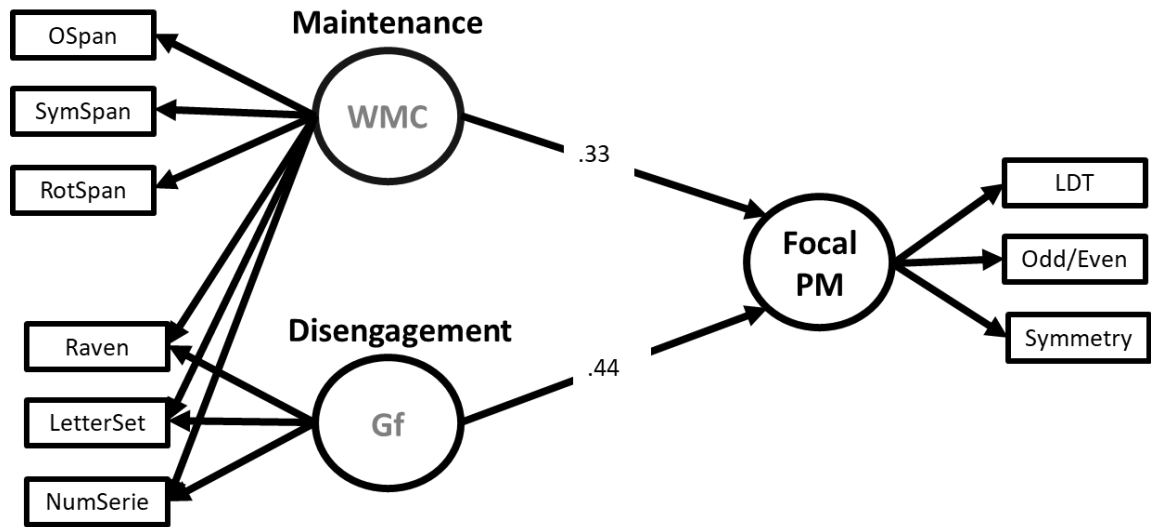


Figure B3. Contributions of maintenance and disengagement to focal prospective memory performance. Figure A4. Model fit was good $\chi^2=42.71$ (20); $p<.05$; CFI=.97; RMSEA = .06. Both the maintenance path and the disengagement significantly predict performance on the non-focal prospective memory factor. In total the two paths predicted 38.5% of the variance in focal prospective memory tasks.

Finally, figure B3 shows that the maintenance and disengagement analysis also yielded similar results in the focal condition as in the non-focal condition discussed above. Interestingly, ‘maintenance’ captured more performance variance in the focal condition than in the non-focal condition, but the relationship between fluid intelligence and performance was only slightly larger. Subsequently, any differences in the relationships between cognitive ability and prospective memory performance between focal and non-focal task conditions are at best a small matter of degree rather than pattern of processes predicting performance.

APPENDIX C

Flanker Deadline Procedure

This task is a modified version of the arrow flanker that uses an adaptive procedure to estimate the subject's threshold. Eighteen blocks of 18 trials each (total 324 trials) are administered. Each trial has a response deadline that limits how long the subject has to respond before hearing a loud beep and forfeiting the opportunity to respond on that trial. This deadline either decreases (less time to respond) if the subject is accurate on at least 15 trials within each block or increases (more time to respond) if their accuracy rate is below that. The first block has a response deadline of 1050 ms. For the first six blocks, the response deadline either decreases by 90 ms or increases by 270 ms for the next block, again depending on if the subject is accurate on at least 15 of the 18 trials. For subsequent blocks, the response deadline either decreases by 30 ms or increases by 90 ms. If after any block the response deadline would be set below 150 ms, it is automatically set to exactly 150 ms. The stimuli remain on the screen up until the response deadline. Each block has 12 congruent and 6 incongruent trials in random order with a randomized 400 – 700 ms ISI. The dependent variable is the response deadline after the final block.

REFERENCES

- Bisiacchi, P.S., Tarantino V., Ciccola, A. (2008). Aging and prospective memory: the role of working memory and monitoring processes. *Aging Clinical and Experimental Research*, 20(6), 569-577.
- Brewer, G. A. (2011). Analyzing response time distributions: Methodological and theoretical suggestions for prospective memory researchers. *Zeitschrift fur Psychologie / Journal of Psychology*, 219(2), 117-124. DOI: [10.1027/2151-2604/a000056](https://doi.org/10.1027/2151-2604/a000056)
- Brewer, G. A., Knight, J. B., Marsh, R. L., & Unsworth, N. (2010). Individual differences in event-based prospective memory: Evidence for multiple processes supporting cue detection. *Memory & Cognition*, 38(3), 304-311.
- Costa, A., Hernández, M., Costa-Faidella, J., & Sebastián-Gallés, N. (2009). On the bilingual advantage in conflict processing: Now you see it, now you don't. *Cognition*, 113, 135-149.
- Craik, F.I.M. (1986). A functional account of age differences in memory. In F. Flix & H. Hangendorf (Eds.), *Human memory and cognitive capabilities: Mechanisms and performances* (pp. 409-422). Amsterdam: Elsevier.
- Chronbach, L. J. & Furby, L. (1970). How We Should Measure "Change"-Or Should We? *Psychological Bulletin*, 74, 68-80.
- Draheim, C., Harrison, T. L., Embretson, S. E., & Engle, R. W. (2017, March 9). What Item Response Theory can tell us about the complex span tasks. *Psychological Assessment*. Advance online publication.
- Duncan, J., Parr, A., Woolgar, A., Thompson, R., Bright, P., Cox, S., & ... Nimmo-Smith, I. (2008). Goal neglect and Spearman's g: Competing parts of a complex task. *Journal of Experimental Psychology: General*, 137(1), 131-148
- Einstein G. O., & McDaniel, M. A. (1990). Normal aging and prospective memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 16, 717-726.
- Einstein, G.O., McDaniel, M.A., Thomas, R., Mayfield, S., Shank, H., Morrisette, N., & Breneiser, J. (2005). Multiple processes in prospective memory retrieval: Factors determining monitoring versus spontaneous retrieval. *Journal of Experimental Psychology: General*, 134, 327-342.

- Engle, R. W., Kane, M. J., & Tuholski, S. W. (1999). Individual differences in working memory capacity and what they tell us about controlled attention, general fluid intelligence and functions of the prefrontal cortex. In A. Miyake & P. Shah Eds. , *Models of working memory: Mechanisms of active maintenance and executive control* pp. 102-134. New York: Cambridge University Press.
- Fukuda, K., & Vogel, E. K. (2011). Individual differences in recovery time from attentional capture. *Psychological Science*, 22, 361-368.
- Kane, M. J., Bleckley, M. K., Conway, A. R. A., & Engle, R. W. (2001). A controlled-attention view of working memory capacity. *Journal of Experimental Psychology: General*, 130(2), 169-183.
- 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), 47-70.
- Kvavilashvili, L., Kornbrot, D. E., Mash, V., Cockburn, J., & Milne, A. (2008). Differential effects of age on prospective and retrospective memory tasks in young, young-old, and old-old adults. *Memory*, 16, 1-17.
- Loft, S., Kearney, R., Remington, R. (2008). Is task interference in event-based prospective memory dependent on cue presentation? *Memory & Cognition*, 36, 139-148.
- Martin, M., Kliegel, M., & McDaniel, M. A. (2003). The involvement of executive functions in prospective memory performance of adults. *International Journal of Psychology: Journal International de Psychologie*, 38, 195-206.
- Maylor, E. A. (1998). Changes in event-based prospective memory across adulthood. *Aging, Neuropsychology, and Cognition*, 5, 107-128.
- Maylor, E. A., Darby, R. J., Logie, R., Della Sala, S., & Smith, G. (2002). Prospective memory across the lifespan. In P. Graf & N. Ohta (Eds.), *Lifespan development of human memory* (pp. 235-256). Cambridge: MIT Press.
- Marsh, R. L., & Hicks, J. L. (1998). Event-based prospective memory and executive control of working memory. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, 24, 336-349.
- McCabe DP, Roediger HL, McDaniel MA, Balota DA, Hambrick DZ.(2010). The relationship between working memory capacity and executive functioning: evidence for a common executive attention construct. *Neuropsychology*, Mar;24(2):222-43.

- McDaniel, M. A., & Einstein G. O. (2000). Strategic and automatic processes in prospective memory retrieval: A multiprocess framework. *Applied Cognitive Psychology, 14*, 127-144.
- McDaniel, M. A., Robinson-Riegler, B., & Einstein, G. O. (1998). Prospective remembering: Perceptually driven or conceptually driven processes? *Memory & Cognition, 26*, 121-134.
- Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex “frontal lobe” tasks: A latent variable analysis. *Cognitive Psychology, 41*, 49-100.
- Morris, C. D., Bransford, J. D., & Franks, J.J. (1977). Levels of processing versus transfer appropriate processing. *Journal of Verbal Learning and Verbal Behavior, 16*, 519-533.
- Roediger, H.L. (1996). Commentary: Prospective memory ad episodic memory. In M. Brandimonte, G. Einstein, & M. McDaniel (Eds.), *Prospective memory: Theory and applications* (pp. 149-155). Mahwah, NJ: Erlbaum.
- Rummel, J., Smeekens, B.A., & Kane, M.J. (2017). Dealing With Prospective Memory Demands While Performing an Ongoing Task: Shared Processing, Increased On-Task Focus, or Both? *JEP: Learning, Memory, & Cognition, 43*, 1047-10062.
- Scullin, M., McDaniel, M. A., & Einstein, G. O. (2010). Control of Cost in Prospective Memory: Evidence for Spontaneous Retrieval Processes. *JEP: Learning, Memory, & Cognition, 36*, 109-203.
- Shelton, J.T. & Christopher, E.A. (2016) A Fresh Pair of Eyes on Prospective Memory Monitoring. *Memory & Cognition, 44*, 837-854.
- Shipstead, Z., Harrison, T. L., & Engle, R. (2016). Working memory capacity and fluid intelligence: Maintenance and disengagement. *Perspectives on Psychological Science, 11*, 771-799.
- Shipstead, Z., Harrison, T., Trani, A., Redick, T., Sloan, P., Bunting, M., Hicks, K., Draheim, C., Engle, R.W. (Submitted). Individual Differences in Cognitive Control: Unitary Working Memory or Diverse Executive Function? *Psychonomic Bulletin & Review*.
- Smith, R. E. (2003). The cost of remembering to remember in even-based prospective memory: Investigating the capacity demands of delayed intention performance. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 29*, 347-361.

- Smith, R. E., Hunt, R. R., McVay, J. C., & McConnell M. D. (2007). The Cost of Event-Based Prospective Memory: Salient Target Events, *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 33, Jul 2007. pp. 734-746.
- Tulving, E., & Thomson, D. M. (1973). Encoding specificity and retrieval processes in episodic memory. *Psychological Review*, 80, 352-373.
- Turner, M. L. & Engle, R. W. (1989). Is working memory capacity task dependent? *Journal of Memory and Language*, 28, 127–154.
- Unsworth, N., Heitz, R. P., Schrock, J. C., & Engle, R. W. (2005). An automated version of the operation span task. *Behavior Research Methods*, 37(3), 498-505.
- Verhaeghen, P. (2000). The parallels in beauty's brow: Time-accuracy functions and their implications for cognitive aging theories. In T. J. Perfect and E. A. Maylor (Eds.), *Models of cognitive aging* (pp. 50-86). Oxford: Oxford University Press.
- Volle, E., Gonen-Yaacovi, G., de Lacy Costello, A., Gilbert, S. J., & Burgess, P. W. (2011). The role of rostral prefrontal cortex in prospective memory: A voxel-based lesion study. *Neuropsychologia*, 49(8), 2185–2198.
- West, R., & Craik, F. I. M. (2001). Influences on the efficiency of prospective memory in younger and older adults. *Psychology and Aging*, 16, 682-696.