The Adaptive Use of Working Memory in Young and Older Adults:
Effects of Incentives and Task Demands

by

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Dedication

To my family

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Abstract

Working memory demands are common in everyday life. Because working memory is costly, we constantly need to judge when it is worth (or not worth) using working memory. Engagement of working memory can be driven by multiple internal and external factors such as ability, motivation, and environment. The present dissertation explores complex interactions between individual differences in ability, internal and external motivational factors, and how these internal processes interact with demands and constraints coming from the task and environment. The first two experiments of the current dissertation (Chapters 2 and 3) examine how young and older adults respond to working memory demands, especially when under loss incentives, and how those responses differ under situations that vary in the degree to which engagement in the task itself may depend on self-initiated vs. task-constrained control. Given that almost every behavior is the outcome of a mix of top-down controlled and automatic bottom-up processes, the last experiment of this dissertation (Chapter 4) investigates whether people adaptively balance (relatively controlled and effortful) working memory and (relatively automatic and implicit) reinforcement learning in response to varying task demands. Overall, we show that high task load and loss incentives lead to adaptive changes in working memory engagement, but those changes can deviate from what is optimal in terms of maximizing performance. Our results also suggest the effects of loss incentives and task demands on working memory engagement can differ for young and older adults and for people with different cognitive ability.

Chapter 1 Introduction

The Costs of Using (or Not Using) Working Memory

Humans are often thought to be cognitive misers (Kool & Botvinick, 2018; Shenhav et al., 2017). When environmental inputs require us to use a lot of cognitive control and working memory, we often "pay for it" with feelings of effort or stress during the task and being fatigued afterward. When asked to choose between a task with a low vs. high level of demand for cognitive effort, people often prefer the low-effort task to the high-effort task (Dunn et al., 2016; Kool et al., 2010). However, not putting forth enough effort often has its own costs, such as a cook who does not keep the proper ingredients, amounts, and cooking times in mind ending up with an unappetizing meal. In contrast, at other times, we may engage working memory and other effortful processes when they are not helpful or can even hurt our performance. For example, in many gambling and reinforcement tasks, pigeons and rats perform better than humans because they rely on simple probabilities, whereas humans often employ cognitive strategies to try to outguess the system (see discussion by Wolford et al., 2004). The present dissertation examines each of these scenarios and how they may differ for young vs. older adults.

Working memory – the ability to hold information in mind while performing processing operations on it or new information – is an ideal testbed for studying how people respond to cognitive demands because it is relatively straightforward to manipulate those demands quantitatively by increasing the number of items to be remembered. In the N-back task (a widely used task for assessing working memory), people demand greater rewards to engage in trials associated with greater cognitive effort, and the costs of mental effort increase parametrically with increasing working memory load (Westbrook et al., 2013).

Moreover, cognitive effort is more costly for older adults than young adults. Older adults need to exert more effort than young adults to initiate and maintain the engagement of working memory (Ennis et al., 2013; Hess et al., 2016; Westbrook et al., 2013). Given the age-related differences in effort costs, answers to the question “when is working memory worth it?” can differ for young and older adults. One related perspective, the selective engagement theory (Hess, 2014), argues that aging is associated with increased mental effort costs, and these increased costs reduce the ratio of benefits to costs for a cognitive task for older adults than younger adults. This leads to a reduced motivation to engage working memory (and other mental resources) for older adults.

Because working memory is costly for young and (more so for) older adults, people often need to be motivated to invest their mental effort. A common way to motivate the use of working memory is to incentivize it. Incentives are usually found to improve cognitive performance in young and older adults, suggesting that people increase their cognitive control when incentives are offered. However, most studies looking at incentive effects on young and older adults have used gain incentives (e.g., Bowen et al., 2020; Cohen et al., 2016; Di Rosa et al., 2019; Spaniol et al., 2014; Thurm et al., 2018; Yee et al., 2019), with only a very few investigating the effects of loss incentives. To bridge this gap, Chapters 2 and 3 in the present dissertation examine the effects of loss incentives on working memory and subjective mental demand in young and older adults, and the effects of environmental variables on whether people may pay those costs either in performance or in their subjective feelings of demand.

Internal and External Factors That Drive Performance: Ability, Motivation, and Environment

Cognitive functioning results from the integration of environmental stimuli and internal processes. Performance on cognitive tasks, therefore, depends on interactions between the ability of the individual, their current cognitive-emotional states, and the constraints from the task. Variations in working memory performance across individuals, for example, can arise from complex interactions between stable individual differences in ability (Unsworth & Engle, 2007), internal and external motivational factors that fuel engagement in the task (Botvinick & Braver, 2015; Braver et al., 2014), and how these internal processes interact with supports and constraints coming from the task and environment (Lindenberger & Mayr, 2014).

A central concept in cognitive psychology is that top-down, goal-driven processing is typically more effortful and costly, whereas bottom-up, stimulus-driven processing is more automatic. Craik and colleagues integrated this idea into the study of memory, especially age differences in memory, with the concepts of self-initiated processing and environmental support (Craik & Lockhart, 1972; Craik & Byrd, 1982). Older adults' memory performance is often impaired when encoding and/or retrieval depend on self-initiated processes, but age-related decline in performance is often reduced or even eliminated by when there is environmental support. The concepts of proactive (the sustained maintenance of goal-relevant information) vs. reactive (transient, stimulus-driven goal reactivation) control follow a similar logic (Braver, 2012)), suggesting that self-initiated, proactive processing requires more attentional resources (and is thus more costly) than reactive processing. Older adults are often thought to have reduced attentional resources, and thus to not engage in self-initiated processing as much as young adults because it has a higher relative cost.

Environmental support (usually in the form of environmental cues that encourage task-relevant processing), is typically thought to reduce the resource cost, and to thus improve performance, especially for older adults. However, environmental support can also have a “dark side” (Lindenberger & Mayr, 2014). First, we may over-rely on it, even when it is not the most efficient strategy. For example, when a task can be solved either by retrieving information from memory or by visually scanning the information from a look-up table on the screen, older adults relied on the more time-consuming visual-scanning strategy. This slowed their performance compared to younger adults, who relied more on the faster memory-retrieval strategy (Rogers et al., 2000). Second, the term “support” is synonymous with “constraint”, and environmental cues that drive engagement in a task may feel more like the latter when they push us to perform tasks that are difficult or aversive. For example, we often find that deadlines help us focus and get more done, but also often find that performing under deadlines feels more demanding than situations that allow us to more freely match our level of performance and effort with our internal motivation.

To understand these complex factors underlying working memory performance, the first two experiments of this dissertation (Chapters 2 and 3) examine how young and older adults respond to cognitive demands, especially when under loss incentives, and how those responses differ under situations that vary in how much self-initiated vs. task-constrained control.

Balancing Controlled and Automatic Processes in Response to Demands

Another axiom of cognitive psychology is that no task is process pure. Instead, almost every behavior is the outcome of a mix of controlled and automatic, top-down and bottom-up processes. In many cases, older adults rely more on automatic processes than do young adults.

For example, older adults perform better in familiarity-based recognition (relatively fast and automatic process) than in recollection-based recognition (relatively controlled process associated with remembering specific context about the original event). However, in other situations older adults may bring in more controlled, top-down processing, potentially to compensate for age-related declines in more bottom-up processes (for dicussion see Lustig & Jang, 2020).

Learning to make the rewarding choice among different options provides a good example of how the balance between more controlled vs. more automatic processes may differ both as a function of ability and task demands. Specifically, choice learning can be supported by both working memory (WM; relatively controlled and effortful) and reinforcement learning (RL; relatively automatic and implicit) (Collins, 2018; Collins & Frank, 2012; Rmus et al., 2021). However, because WM is fast but capacity-limited and RL is robust but slow, these choice-learning situations also present an interesting situation in which increasing WM load (the number of stimulus-response options to be learned) may not only lead to worse performance but also influence the degree to which people rely on (relatively controlled) WM vs. (relatively automatic) RL processes.

To understand how people balance controlled and automatic processes in response to demands, Chapter 4 of the current dissertation examine the adaptive nature of combining working memory and reinforcement learning in choice learning in response to varying task loads and investigate if people use computationally optimal balance (Lewis et al., 2014).

Summary and Overview

In this dissertation, we first examine young and older adults' objective performance and subjective responses to the costs of using – or not using – working memory in two tasks that differ in the degree to which their structure supports (or constrains) engagement (Chapters 2 and 3). In the third study, we examine how people balance effortful WM processes with more automatic RL processes as demands increase. Taken together, we show that high task load and loss incentives lead to adaptive changes in working memory engagement, but those changes can deviate from what is optimal in terms of maximizing performance. Our results also suggest the effects of loss incentives and task demands on working memory engagement can differ for young and older adults and for people with different cognitive ability.

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Chapter 2 Losing Money and Motivation: Effects of Loss Incentives on Motivation and Metacognition in Younger and Older Adults

Introduction

In the last 10 years, there has been rising interest on the effects of monetary incentives on cognition. That interest was sparked in part by the integration of cognitive and computational perspectives on reinforcement learning and has spread to the effects of incentive on other aspects of cognition. The general assumption is that incentives increase motivation, and that motivation in turn increases the engagement of attention and cognitive control (Botvinick & Braver, 2015; Yee & Braver, 2018). A great deal of progress has been made on this topic in a relatively short period of time. However, several important gaps in the literature remain.

First, most studies have built on the reinforcement learning literature and implemented incentives on a within-subjects, trial-wise basis (i.e., comparing performance on rewarded vs unrewarded trials). A common finding in that literature is that older adults show reduced neural responsivity to anticipated losses, but similar results to young adults for anticipated gains, experienced gains, and experienced losses (reviewed by Samanez-Larkin & Knutson, 2015). Trial-wise incentive manipulations likely translate well to real-world reinforcement learning and value-based decision making (e.g., after repeated exposures one learns that Restaurant A is more likely to produce a rewarding experience than Restaurant B). However, in these cases, as well as in studies examining the prioritization of high- versus low-value items in episodic memory (Castel et al., 2002; Cohen et al., 2016), incentive valence and magnitude attach to specific items, actions, or decision options.

It’s not clear that conclusions from these more specific, trial-wise incentive manipulations apply to most real world (e.g., school, work, or sports) situations with incentivized performance. For example, a junior accountant performing an audit would likely receive bonus pay for completing all the steps needed thoroughly and efficiently (or have their pay docked for underperforming), rather than having one step be associated with bonus pay for correct completion, another step associated with lost pay for failure (e.g., Libby & Lipe, 1992). The same is likely true in many cognitively challenging situations in everyday life: following directions to reach a desired location, debugging a computer program, or organizing a weekly work schedule for oneself or a group of employees.

Second, many of these real-world situations rely heavily on working memory, and age differences in working memory are both large and a topic of central interest in both theoretical work and empirical studies of cognition and performance (see Park & Festini, 2017 for a recent review). However, most performance-incentive studies have focused on measures related to attention and cognitive control (Di Rosa et al., 2015; Schmitt et al., 2015, 2017; Williams et al., 2017, 2018; Yee et al., 2019), and only a handful have compared young and older adults. As noted above, there have also been a number of reinforcement learning and episodic memory studies focusing more on the ability to learn reward/loss associations or prioritize high vs low reward items (e.g., Castel et al., 2002; Cohen et al., 2016), as well as studies on incentivized episodic memory encoding (e.g., Geddes et al., 2018; Spaniol et al., 2014).

To our knowledge, only one study has examined the effects of incentive on working memory in both younger and older adults (Thurm et al., 2018). The lack of studies on how incentives might affect working memory performance in younger and older adults stands in contrast to the training and neurostimulation literatures, where working memory is a frequent target because of its large age differences and importance in everyday life (Basak et al., 2008; Buschkuehl et al., 2008; Di Rosa et al., 2019; Li et al., 2008; Rhodes & Katz, 2017; Stephens & Berryhill, 2016). From a scientific perspective, another reason to examine working memory is that the range of set sizes used in many working memory tasks also provides a relatively straightforward way of examining whether age differences in the response to incentive vary as a function of task load.

Third, many studies have focused on reward (gain) incentives (e.g., Bowen et al., 2020; Castel et al., 2002; Cohen et al., 2016; Di Rosa et al., 2019; Spaniol et al., 2014; Thurm et al., 2018; Yee et al., 2019). However, loss is thought to play an increasingly important part in older adults' experience, and real-world attempts to motivate their behavior often focus on the opportunity to avoid such losses (e.g., of health, of employment or financial stability, of driving privileges). Finally, the assumption that incentive will increase motivation (and then increase attention and control) is rarely tested directly. This is despite an earlier literature indicating that extrinsic motivators such as monetary incentive can often have paradoxical effects (see meta-analytic reviews by Cerasoli, Nicklin, & Ford, 2014; Deci, Koestner, & Ryan, 1999).

The present study begins to address some of these gaps. We examined the effects of loss incentive, implemented across the entire session, on both younger and older adults. We examined both working memory performance and subjective reports of related constructs including perceived demand, frustration, motivation, distraction, and metacognition. We focused on losses both because they have been understudied, and because different theoretical perspectives make competing hypotheses about the effects of loss incentives on older adults, whereas predictions are the same (and thus the incentive manipulation less incisive) for reward (gain) effects. The subjective measures were used to provide potentially converging or disconfirming evidence for each of these views.

Before describing the rationale for our study, we review different theoretical perspectives that make disparate predictions for the effects of loss on older adults' cognitive performance and subjective response. The major predictions for each view are summarized in Table 2-2.

First, *the intuitive prediction* is that incentive increases motivation, which increases performance. This might also be expected to reduce perceived demand and increase metacognitive accuracy, as participants pay closer attention to their performance in order to improve it. Building off of lifespan development theory and the idea that losses become more prominent in later life, the *motivational shift* hypothesis is that older adults are particularly motivated to avoid losses: "With advancing age, however, personal goals are expected to shift towards an increasingly stronger focus on maintenance and prevention of loss" (Freund & Ebner, 2005). If one follows the logical chain, described above – that greater motivation should increase the application of cognitive control and thus increase performance – this hypothesis would seem to suggest that older adults would show even larger performance and motivation increases in the loss condition than do young adults.

However, the motivational shift theory appears to primarily apply to older adults' goal-setting and preferences in decision-making scenarios, and in particular whether one gravitates towards opportunities for growth and improvement in cognitive or physical performance versus maintenance or compensation for loss on those fronts (e.g., Best & Freund, 2018; Freund & Ebner, 2005). It may also be of relevance in avoidance-learning paradigms, where older adults have sometimes shown faster learning in response to loss (Eppinger & Kray, 2011; Frank & Kong, 2008; Hämmerer et al., 2011). It does not seem to straightforwardly apply to the motivation-cognitive performance questions of interest here. Indeed, those studies that have examined the effects of loss incentive on older adults' response to cognitive demands are relatively consistent in showing that older adults have either an equivalent or reduced response to loss incentive compared to young adults and/or to positive incentive (e.g., Bagurdes et al., 2008; Di Rosa et al., 2015; Pachur et al., 2017; Schmitt et al., 2015, 2017; Williams et al., 2017, 2018). Thus, while we note that the motivational shift hypothesis might superficially appear to predict larger performance improvements, greater motivation, and increased metacognitive accuracy for older adults in the loss condition, we do not consider it likely to apply to the current study.

Most of the studies finding apparently reduced sensitivity to loss incentives in older adults have interpreted it as an example of the *positivity effect* – the finding that older adults tend to prioritize positive, and de-prioritize negative, information for attention and memory (Bagurdes et al., 2008; Di Rosa et al., 2015; Pachur et al., 2017; Williams et al., 2017, 2018). This interpretation of the positivity effect would seem to predict that compared to young adults, older adults should show less effects of loss incentive (results more similar to the control condition) on both our performance and subjective measures.

However, some caution is needed in making that leap. As noted above, in some situations older adults are in fact even more responsive to loss than are young adults (Eppinger & Kray, 2011; Frank & Kong, 2008; Hämmerer et al., 2011). The apparent reduction in sensitivity to loss in some other studies may be at least partially an artifact of how incentive cues were implemented in those experiments. In most cases, the reduced loss sensitivity of older adults primarily concerns neural or electrophysiological responses to the incentive cue. Overall performance quality often shows similar incentive effects for the two age groups, though there may be some differences in speed-accuracy tradeoffs (e.g., Schmitt et al., 2015; Williams et al., 2017, 2018). This suggests that older adults may be less responsive to loss-incentive cues, but equally (and in some cases, even more so) responsive to the actual delivery of loss incentive. That interpretation would fit with findings from the reinforcement learning literature that older adults have reduced neural and arousal responses to loss cues, but equivalent or greater responses to loss delivery (reviewed by Samanez-Larkin et al., 2007).

Similar results indicating potentially greater responses by older adults to loss delivery have been reported in the Monetary Incentive Delay task (Kircanski et al., 2018). In addition, using an analysis approach that emphasizes spatiotemporal covariance patterns, Spaniol and colleagues (2015) found that at cue presentation, young and older adults showed similar reward-network recruitment, but older adults showed increased recruitment of frontal-parietal control networks and decreased deactivation of the default network; these effects did not differ by valence. At the point of feedback/incentive delivery, young and older adults again showed similar patterns related to general feedback/reward processing, but older adults recruited two additional networks in response to error feedback and to loss (Bowen et al., 2019).

A neuroimaging study by Geddes et al. (2018) generally replicated the pattern of a specific reduction in older adult's activation of reward networks in response to loss cues for the Monetary Incentive Delay task, but a different pattern for incentivized encoding trials for an upcoming (24 hour delay) recognition memory test. Behaviorally, young adults showed incentive (reward or punishment) advantages on recollection but not familiarity; older adults had low recollection performance and no effects of incentive (see Spaniol et al., 2014 for slightly different results as well as the Geddes et al. discussion of the similarities and differences between these studies). Interestingly, the neuroimaging data showed similar activations of memory- and reward-related region in both young and older adults during the incentive cue, regardless of incentive valance, but reduced engagement of these regions by older adults during the encoding period. The authors suggest that differences between their memory task versus the Monetary Incentive Delay task as well as value-directed memory tasks in terms of the immediacy of feedback/incentive manipulation – and thus the ability to modulate processing in response – might partially explain the differences in results.

In short, whether older adults show the same, less, or more responsivity to loss than do young adults seems to vary widely across different paradigms. A more nuanced view of the positivity effect, integrated with the concepts of proactive versus reactive control, may provide a more comprehensive explanation for the patterns seen across different tasks. Both theoretical and empirical work indicate that the age-related positivity effect is primarily seen in low-constraint situations that allow or require older adults to direct their attention towards or away from emotional information (see Carstensen & DeLiema, 2018; Reed & Carstensen, 2012 for reviews). It does not usually occur when negative information is highly salient or otherwise processed relatively automatically. Likewise, the Dual Mechanisms of Control theory's perspective on aging is that older adults are less likely than young adults to engage self-initiated proactive control to prepare for upcoming cognitive demands, but often show even greater (perhaps compensatory) reactive control when the critical stimulus is presented (Braver, 2012; see earlier work by Craik & Byrd (1982) for similar ideas on age differences in self-initiate processing). Thus, in many previous studies using trial-by-trial incentive cues, older adults may have failed to engage with the loss cues at presentation. This could explain the failure to show the same neural or physiological responses to those cues as did young adults. Notably, one study using block-wise presentation of incentive cues found if anything increased sensitivity to loss cues in older adults, suggesting that experienced (rather than merely anticipated) losses carried over to subsequent trials (Schmitt et al., 2017).

It has been suggested that when negative information is unavoidable, older adults may instead disengage or distance themselves from the situation, and in addition may later reframe the situation to take a more positive view (Charles, 2010). For example, Charles & Carstensen (2008) found that after participants listened to conversations ostensibly consisting of disparaging remarks about them, young adults wanted to learn more about the cause of the complaints and made more appraisals about the speakers, whereas older adults distanced themselves from the situation with remarks such as "you can't please all the people all the time". Compared to incentive cues, the actual delivery of loss feedback – especially performance-based incentives in a domain (memory) that is important to older adults (Dark-Freudeman et al., 2006; Reese et al., 1999) may be more personally relevant and thus difficult to ignore, and paradoxically lead older adults to disengage from the situation rather than increasing their motivation to improve (but see Barber et al., 2015; Barber & Mather, 2013 for evidence suggesting a nonlinear relationship).

A related proposal from Selective Engagement Theory (SET; Hess, 2014) is that a person's motivation to engage depends on their calculation of benefits vs. costs of that engagement, and that those costs – and thus the likelihood of disengagement – may occur at earlier levels of objective task difficulty for older adults. Although to our knowledge Hess and colleagues have not directly addressed the question of monetary incentives, if losses after errors incentives magnify the perceived costs of performance, they would be predicted to increase the likelihood of disengagement. Consistent with this idea, previous studies in our lab using an attention task found that loss incentives reduced focused-attention performance and increased self-reported mind-wandering in older adults (Lin, 2018; Lin, Berry, & Lustig, 2019).

An alternative, more competitive pathway to disengagement has been suggested by Ferdinand & Czernochowski (2018): Processing incentive information may itself create a cognitive load that draws cognitive processing away from the task itself. Thus, incentive could paradoxically reduce performance, with effects presumably most evident at the highest working memory loads. Alternatively, as suggested in some of their papers, the cognitive load of the task itself may cause older adults to ignore or less completely process incentive information (Schmitt et al., 2015, 2017). Thus, the predictions that this view would make for many of the measures in the current study are not entirely clear. As a first step towards testing this possibility, we asked participants about the degree to which they found the feedback (control or incentive) provided to them to be distracting.

Table 2-1. Demographics and self-reported Poor Attentional Control

		Young Control (*n* = 43, 31 f)	Young Loss (*n* = 42, 30 f)	Old Control (*n* = 41, 24 f)	Old Loss (*n* = 43, 28 f)
Age					
	mean	20.19	19.79	71.37	71.95
	SD	1.93	2.06	6.83	6.39
Years of Education					
	mean	14.40	14.04	17.45	17.21
	SD	1.53	1.42	2.11	2.30
ERVT					
	mean	19.65	17.95	29.51	30.33
	SD	5.88	4.73	9.04	8.41
PAC Mind-Wandering					
	mean	14.58	15.86	12.15	12.47
	SD	4.29	3.06	3.06	3.06
PAC Boredom					
	mean	13.72	14.81	10.51	10.79
	SD	3.51	3.37	2.66	2.72
PAC Distractibility					
	mean	15.42	15.67	12.39	13.79
	SD	3.53	4.18	3.12	3.94
MMSE					
	mean	n/a	n/a	28.83	28.95
	SD	n/a	n/a	1.18	1.11

f: Female, ERVT: The Extended Range Vocabulary Test, PAC: The Poor Attentional Control scale

Table 2-2. An overview of the predictions from each of the theoretical perspectives

Perspective	**Actual Performance**	**NASA-TLX measures**	**SAMQ and IMI**	**Other**
Intuitive view (greater motivation and cognitive control under incentive)	Better in incentive condition	Performance: More accurate metacognition in incentive condition Demand: Lower in incentive condition Effort: Higher in incentive condition Frustration: No strong predictions; loss may lead to greater frustration at higher set sizes	Greater motivation in incentive condition Weak prediction for greater pressure/tension in incentive condition	
Motivational shift (older adults especially motivated by losses)	Generally the same as the "intuitive" hypothesis but with larger effects for older adults			
Heuristic positivity effect (older adults ignore negative information including losses)	Generally the opposite of the "motivational shift" hypothesis; older adults *less* responsive to the loss incentive. Potentially less accurate metacognition (NASA-TLX Performance and IMI Perceived Competence) for older adults in the loss condition, if they are ignoring loss-related feedback.			
Nuanced positivity effect (older adults have reduced proactive, increased reactive responses to negative information; potentially followed by reframing)	Reduced performance for older adults in loss condition	Demand: Higher in loss condition Effort: No differences or reduced for older adults in loss condition Frustration: Increased by loss	Reduced motivation for older adults in the loss condition Reframing may inflate IMI Competence scores	Reframing may reduce long-term metacognitive accuracy for older adults in the loss condition
Incentive as cognitive load	Reduced performance under loss incentive, especially for older adults and at higher set sizes	Performance: If performance monitoring competes with the task itself for cognitive processing, ratings may be less accurate under loss incentive, especially at higher set sizes. Demand: Higher in loss condition, especially for older adults and at higher set sizes	Increased self-reported distraction in loss condition	

NASA-TLX: NASA Task Load Index, SAMQ: State Attention and Motivation Questionnaire, IMI: Intrinsic Motivation Inventory

Method

Rationale and overview of methods for the present study

As noted earlier, although the number is small, there have been several studies examining age differences in the response to loss incentives on cognitive control tasks using the trial-based incentive cue method borrowed from reinforcement learning paradigms. These have generally indicated a reduced responsivity to loss cues in older adults, although that reduced responsivity is typically most evident on neural or physiological measures, rather than performance. Although these studies are interesting and important, it was not our goal to add another variation.

Instead our aim was to take a first step towards closely related questions that have been thus far largely unaddressed. We used a session-wide incentive manipulation rather than trial-wise changes, since as noted above session-wide incentives are more likely to reflect real-world situations. We examined working memory, which thus far has been the focus of only one age × incentive study, despite the importance of working memory to cognitive performance in many domains, and its well-known decline in aging. We focused on losses, rather than gains, since this again has been a neglected area despite the putatively increased importance of loss in later adult life, and because most of the theoretical perspectives above have the same predictions for rewards/gains but differ in their predictions for losses, making the latter more incisive.

Based in part on other data from our lab suggesting that loss incentive reduced focused attention in older adults and increased mind-wandering (Lin et al., 2019), we were especially interested in the possibility that loss incentives might lead older adults to disengage from the task. Our task and procedures thus closely followed those previously used by Hess et al. (2016) which examined age differences in a physiological measure of task engagement as a function of working memory load. We used largely the same working memory task and questionnaires to assess self-reported mental demand, effort, and related constructs such as frustration, and added the loss-incentive manipulation. This also allowed our control sample to provide a basic replication test of the behavioral age differences reported by Hess et al., 2016. Finally, we added an exploratory set of subjective measures of motivation, distraction and metacognition as a first step towards examining the effects of loss incentives on these constructs in young and older adults.

Participants

85 young adults and 84 older adults were included in the analysis (Table 2-1; see Supplemental Material S8 for exclusion information). Young adults (61 female, mean age = 19.99 years, range = 18-29) were students recruited from the University of Michigan. Older adults (52 female, mean age = 71.67, range = 60-88) were recruited from the Ann Arbor community. Participants were screened to ensure physical and psychological health with no history of anxiety, depression, ADHD, or head injury, and no use of medications that could affect cognition. As in other studies in our lab, the Extended Range Vocabulary Test Version 3 (ERVT; Ekstrom, 1976) was used to screen for participants who might not understand the instructions or were generally unmotivated or not willing/able to complete the experimental session; a minimum score of 9 out of a possible 48 was required. For older adults, a Mini Mental State Examination score (MMSE; Folstein, Robins, & Helzer, 1983) of 27 or greater was required. Young and older adults received $10 and $12 per hour respectively for their participation (older adults received a slightly higher amount to compensate for their driving to the testing site). Written informed consent was obtained from all participants. The study was approved by the Institutional Review Board (IRB) of the University of Michigan.

Design

Age group (young, old) and incentive condition (control, loss) were the group-level, between-subjects variables; set size was a within-subjects variable of secondary interest. Participants within each age group were randomly assigned to the control or loss condition. Our previous study using an attention task (Lin et al., 2019) found an effect size of f = .217 (equivalent η_p^2 = .045) for the age (young vs. old) by motivation (control vs. loss) interaction on task performance. Power analysis using *G*Power* (Faul et al., 2007) suggested a total sample size of 169 to detect the age by motivation interaction with an effect size f of .217; α error probability of .05; power (1-β probability) of .80; numerator degrees of freedom of 1; 4 groups in a two-way ANOVA. For the exploratory correlation analyses within each group, a sensitivity analysis indicated r of .304 was the minimum to be detected at .80 power.

Working Memory Task

The Letter Number Sequencing (LNS) task from the Wechsler Adult Intelligence Scale-III (Wechsler, 1997) was used to measure working memory. The task was programmed using PsychoPy version 3 (Peirce, 2007). On each trial, participants received intermixed letters and numbers at a rate of one item per second. Participants were asked to report the numbers in numerical order, the letters in alphabetical order. Each run had 6 trials of the same set size (the number of items to be memorized). Set size increased in an ascending order across runs, from set size 2 (run 1) to set size 9 (run 8). There were 8 runs total. At the end of each run, participants were given performance feedback (percent correct/incorrect for a given run). For interactions with the within-subjects variable set size, sensitivity analyses indicated power of .80 for f = .111, which is equivalent to η_p^2 = .012 (4 groups, 8 measures, *r* = .217 between measures; nonsphericity correction set at 1).

Questionnaires

All questionnaires were self-administered after the instructions for it were provided by the experimenter, and the participant given the chance to ask any questions.

Poor Attentional Control (PAC) Scale

The PAC scale serves as a trait measure of attentional function in everyday life. It was administered before the LNS task to avoid the possibility that participants' perceptions of their performance might influence their responses. The PAC subscale consists of 15 items identified by factor analysis (Huba et al., 1982) from the larger 36-item Imaginal Processes Inventory (Singer & Antrobus, 1970). As in previous studies in our lab (e.g., Berry, Demeter, et al., 2014; Berry, Li, Lin, & Lustig, 2014; Kim, Müller, Bohnen, Sarter, & Lustig, 2017) participants completed all 36 items so that they were viewed in context, with analyses focused on the PAC scale items. For each item, the participant indicated how true the statement was of them (1 = *not all true of me*; 5 = *very true of me*).

NASA Task Load Index (NASA-TLX)

The NASA-TLX measures subjective workload experienced during the task (Hart & Staveland, 1988). It was administered after each LNS run, and it has 6 subscales that ask 1) How mentally demanding was the task? (Mental Demand); 2) How physically demanding was the task? (Physical Demand); 3) How hurried or rushed was the pace of the task? (Temporal

Demand); 4) How successful were you in accomplishing what you were asked to do? (Performance); 5) How hard did you have to work to accomplish your level of performance? (Effort); 6) How insecure, discouraged, irritated, stressed, and annoyed were you? (Frustration). The responses are rated on a 0 (*very low*) to 100 (*very high*) point scale, except for the Performance scale which uses a "reversed" scale, 0 (*successful*) to 100 (*failure*). In the results and figures below, we present the results for the Performance scale using the more intuitive 0 (*failure*), 100 (*success*) format.

State Attention and Motivation Questionnaire (SAMQ)

The SAMQ was administered after finishing the LNS task and the final NASA-TLX form. It was created by our lab to ask "state" questions related to boredom, difficulty focusing attention, distraction, and motivation using the same wording as the "trait" level PAC scale. It has been shown in several previous studies to correlate with both the PAC trait measures and with construct-related performance measures (e.g., Berry, Demeter, et al., 2014; Berry, Li, Lin, & Lustig, 2014; Kim, Müller, Bohnen, Sarter, & Lustig, 2017). The version used in the present study modified the last two questions to specifically assess the distracting or motivating potential of monetary incentive: "I found the possibility of [*Control*: getting feedback; *Loss*: losing money] to be distracting"; "I found the possibility [*Control*: getting feedback; *Loss*: losing money] to be motivating." (See Supplemental Material S4 for full questionnaire.)

Intrinsic Motivation Inventory (IMI)

The IMI is a standard 22-item questionnaire assessing participants' subjective experience regarding a task in an experiment (Ryan, 1982). After completing the task and SAMQ, participants completed the IMI, indicating how true each statement was for them during the LNS task (1 = *not all true*; 7 = *very true of me*). This inventory has four subscales: Interest/Enjoyment, Perceived Choice, Perceived Competence, and Pressure/Tension. Interest/Enjoyment is often used as a self-report measure of intrinsic motivation.

Procedure

Participants completed informed-consent procedures, a health and demographic survey, and the PAC questionnaire. Participants then received instructions for the LNS task, and completed a practice run consisting of 5 trials of set sizes of 2 to 5. Participants had to get more than 80% correct on the practice trials to proceed to the main task. If not, they repeated the practice. Failure to reach criterion within three practice runs terminated the session (n = 5 older adults).

After the practice run, participants in the loss condition were endowed with $24. This money was put on the table in front of them. They were told that it was theirs to keep for good performance (in addition to the hourly compensation for study participation), but that 50 cents would be deducted for every incorrect trial. Both performance feedback (percent incorrect) and incentive feedback (the amount of money lost) were given after each run. After that, the experimenter immediately removed the amount lost and placed the new amount on the table. Control participants were given performance feedback only. Participants next completed the NASA-TLX with reference to the run they had just completed.

After the final LNS run and corresponding NASA-TLX questionnaire, participants completed the SAMQ and IMI to assess their evaluation of their attention, motivation, and performance during the task as a whole. They next completed the Mini-Mental State

Examination (MMSE; Cockrell & Folstein, 2002; older adults only) and AD8 (Galvin et al., 2005; older adults only), and Extended Range Vocabulary Test (ERVT; Ekstrom, 1976), and were thanked, debriefed, and given the hourly compensation for their participation.

Analyses

Analyses were conducted using R version 3.6.1 (R Core Team, 2017). Our overall analysis strategy followed that of Hess et al. (2016) in examining effects of age group and set-size, with the additional between-subjects variable of incentive condition (control, loss). As described below, we also used correlation analyses to assess the relative accuracy of participants' metacognitive reports.

The primary question was whether/how the loss-incentive would affect the dependent measures of performance, motivation, and metacognition, and whether incentive effects interacted with age group and/or set size. See Table 2-2 for an overview of the predictions from each of the theoretical perspectives described in the Introduction; critical hypotheses are discussed in more detail below. A secondary question was whether we would replicate the age group and set size effects reported by Hess et al. (2016), especially for participants in the control condition (see Supplemental Material for these analyses). In some cases, especially for unexpected findings, we conducted additional post hoc analyses to provide potentially converging or disconfirming evidence, or to give insight into potential mechanisms.

LNS Task Performance and Subjective Task Load (NASA-TLX)

The LNS data were analyzed using a mixed ANOVA design, with incentive and age group as the between-subjects variables, set size as the within-subjects variable. Greenhouse-

Geisser corrected df, *F*, and *p* values are reported where the sphericity assumption was violated. For easier reading, df values are rounded to the nearest integer in the text.

As in Hess et al. (2016), the NASA-TLX data were analyzed using multi-level modeling (MLM), rather than ANOVA, because the questions were consistently presented in the same sequential order, making the scales non-independent[1]. Included predictors were age group (young adults = referent), incentive condition (control = referent), linear and quadratic trends of set sizes (centered at 5.5), and all interaction terms. To control for individual variability, we included the random intercept for each individual (Field et al., 2012).

Post Task Motivation

The SAMQ questions regarding distraction (Q5) and motivation (Q6) were of primary interest for the present study; the other questions were included to be consistent with other publications from our lab that have used the questionnaire (Berry, Demeter, et al., 2014; Berry, Li, et al., 2014; Lin et al., 2019), allowing interested readers or eventual meta-analyses to compare across experiments and study populations. The IMI subscales were used as post-task, holistic measures of participants' metacognition and emotional-motivational response to the task, as compared to the run-specific questions presented by the NASA-TLX. Both the SAMQ and IMI subscales were analyzed using ANOVA with incentive condition and age group as between-subjects variables.

[1] One might question whether the LNS runs were truly independent given previous findings suggesting that ascending set-size presentation leads to both practice effects, differentially affecting young adults, and proactive interference, differentially affecting older adults (e.g., Lustig, May, & Hasher, 2001; May, Hasher, & Kane, 1999; Rowe, Hasher, & Turcotte, 2008). As a precaution we also used MLM to analyze the LNS results; conclusions did not differ between the two methods.

Correlations between questionnaires and task performance

The NASA-TLX "Performance" scale asked participants to rate their performance on a 0-100 scale immediately after completing the run and receiving feedback. It therefore provides a relatively specific, 'in the moment' assessment of the participants' metacognitive judgment of their performance. The IMI "Competence" scale measures a similar construct, but post-task, and in a more general sense (sample questions: "I think I did pretty well at this task, compared to my peers"; "I am satisfied with my performance on this task"). We used correlation analyses to examine whether age or incentive changed the relationship between these measures (NASA-TLX Performance and IMI Competence) and actual performance. Correlations between these measures and actual performance provided an estimate of participant's *relative* metacognitive accuracy. That is, stronger positive correlations between these measures and actual performance would indicate that those individuals who gave themselves high ratings relative to others in their group did in fact tend to obtain higher scores than others in their group. Fisher's *z*-tests were used to test our a priori question of potential differences in correlation strengths between the groups.

The NASA-TLX Performance scale, with a range from 0-100, also allows for calculation of *absolute* metacognitive accuracy, or the distance between a person's actual performance, and their rating of their performance on the NASA-TLX scale (e.g., if four people all had an actual score of 75% correct, those rating themselves at either 77 or 73 would have better absolute accuracy than those rating themselves at 65 or 85). To measure this, we calculated a "metacognitive difference score" for each run by subtracting the participant's NASA-TLX Performance rating on that run from their actual performance. The metacognitive difference scores were analyzed using the same MLM design as used to analyze the NASA-TLX scales.

We included this as a post-hoc analysis to explore the unexpected finding that participants in the loss condition gave themselves higher ratings for performance. However, in hindsight, it provides an additional test of the version of the "positivity effect" sometimes used to explain the results of previous studies: If older adults in the loss condition are ignoring the feedback information provided at the end of each run, they should be less accurate than the other groups.

Results

Loss incentives increase perceived performance but not actual performance in the working memory task

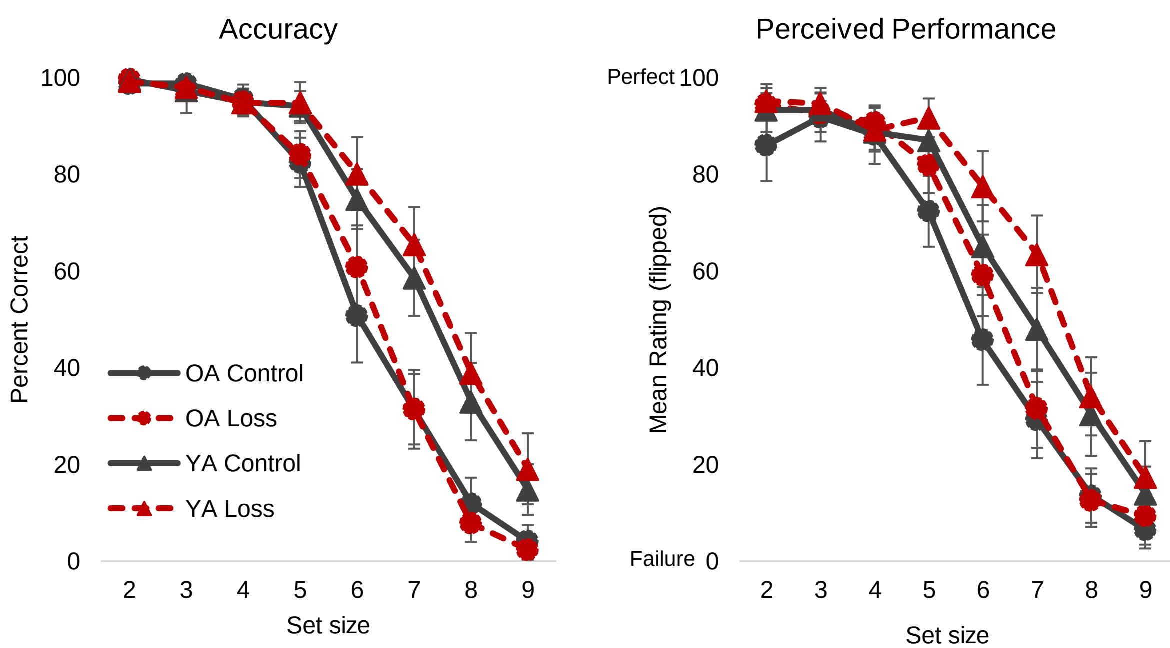
Loss incentive did not affect LNS performance, $F(1, 159) = 1.27$, $p = .262$, $\eta_p^2 = .008$; nor did it interact with age, $F(1, 159) = .56$, $p = .455$, $\eta_p^2 = .003$, or set size, $F(4, 159) = 1.26$, $p = .281$, $\eta_p^2 = .008$ (Figure 2-1). We replicated commonly observed set size and age effects and interactions: Accuracy decreased as set size increased, $F(4, 159) = 879.29$, $p < .001$, $\eta_p^2 = .84$; older adults showed lower accuracy compared to young adults, $F(1, 159) = 67.80$, $p < .001$, $\eta_p^2 = .29$; and older adults' accuracy decreased at earlier set sizes than young adults', $F(4, 159) = 26.88$, $p < .001$, $\eta_p^2 = .14$.

As an exploratory analysis of potential incentive effects on metacognition, we examined participants' self-ratings on the Performance subscale of the NASA-TLX, administered after each run. The full MLM results for the Performance subscale and all NASA measures can be found in Table 2-3. To briefly summarize the critical results, in contrast to the lack of incentive effects on actual performance, participants in the loss condition perceived themselves to be more successful in accomplishing the task than did those in the control condition, $\beta = 8.28$, $t(165) = 2.66$, $p < .01$. (Figure 2-1).

The results so far indicate that loss incentives do not improve performance, contradicting the intuitive hypothesis. As we describe in the Discussion, in hindsight this may not be surprising given the task constraints (relatively fast presentation of stimuli, verbal response required on every trial) and that several other studies have failed to find incentive effects on performance; Hess et al (2016) also did not find effects of an alternative motivation manipulation on this same task. More importantly, we did not find any evidence in either actual or perceived performance that older adults were any more (motivational shift hypothesis) or less (heuristic positivity effect hypothesis) sensitive to the loss incentive.

The higher Performance self-ratings in the loss condition were an unexpected finding, which we discuss in the context of the other metacognitive measures below. Before turning to those issues, we review the results for the other NASA-TLX subscales and post-task questionnaires.

Figure 2-1. LNS accuracy and NASA-TLX perceived performance ratings



Different colors/lines (control = black solid line, loss = red dashed line) and shapes (triangle = young adults (YA), circle = older adults (OA)) are used to highlight the different conditions. Error bars represent 95% confidence intervals. NASA-TLX: NASA Task Load Index

Table 2-3. NASA-TLX MLM results

Effect	Mental demand	Physical demand	Temporal demand	Performance	Effort	Frustration
Intercept	45.69***	9.32***	32.36***	74.20***	44.67***	24.97***
Age	-0.49	5.95*	7.26	-14.12***	2.56	9.06*
SS_{linear}	10.08***	1.00***	7.30***	-12.07***	9.46***	5.40***
$SS_{quadratic}$	0.33	0.09	0.77***	-1.76***	0.34	0.35
Age × SS_{linear}	0.51	1.59***	2.77***	-1.64**	1.04*	3.93***
Age × $SS_{quadratic}$	0.32	0.08	-0.12	0.63*	0.47	0.02
Incentive	-2.49	-2.71	-1.09	8.28**	0.65	3.19
Age × Incentive	-0.37	-2.70	-0.66	-1.86	-4.24	-1.95
SS_{linear} × Incentive	1.11*	0.55	-0.86	0.90	0.65	1.53**
$SS_{quadratic}$ × Incentive	0.24	0.20	-0.01	-0.54	0.03	-0.04
Age × SS_{linear} × Incentive	-0.28	-1.59**	0.36	-1.43	-0.60	-0.92
Age × $SS_{quadratic}$ × Incentive	0.22	-0.09	0.25	0.24	0.05	0.31

**** $p < .001$, ** $p < .01$, * $p < .05$, NASA-TLX: NASA Task Load Index, MLM: Multilevel model, SS: Set size*

Loss incentives increase the perceived demands and frustration at higher task loads but not the effort to meet that demand

The main measures of interest for the NASA-TLX were the Mental Demand, Effort, and Frustration subscales. Hess et al. (2016) noted that the Mental Demand and Effort scales were especially related to the construct of engagement, both in terms of face validity and in their ability to predict a physiological measure of engagement (systolic blood pressure (SBP) reactivity). As noted in

Table 2-2, an intuitive "incentive increases motivation" perspective predicts that incentive should increase the effort people put in to maintain performance as actual demand (set size) increases, and may also reduce perceived demand (i.e., people may perceive the task as less demanding if they are strongly motivated). In contrast, a "disengagement" perspective predicts a lack of willingness to increase effort in response to an increase in perceived demand.

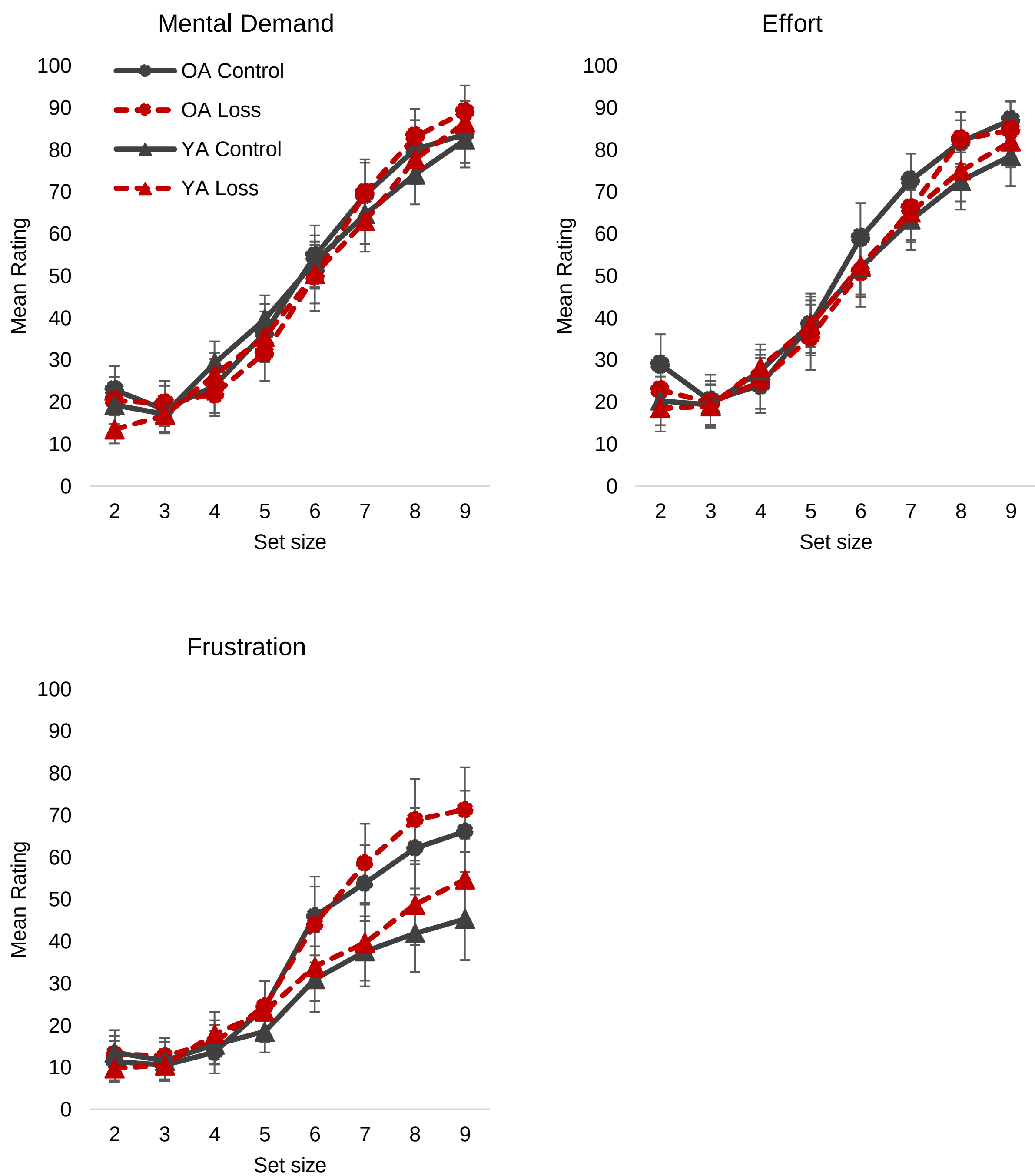
The results were more consistent with the disengagement perspective. For the Mental Demand measure, the Incentive × Set size interaction was significant (Table 2-3) with participants in the loss condition giving numerically lower ratings of demand until about set size 6 and giving numerically higher ratings from set size 8. (Figure 2-2; see also S2, which shows the results more clearly by collapsing across age group.) Post-hoc *t*-tests suggested that this interaction is due to significant increase in ratings from set size 8 to set size 9 in the loss group ($t(168) = -2.35$, $p = 0.019$), but not in the control group ($t(166) = -1.71$, $p = 0.087$). In contrast, for the Effort measure, there was no effect of incentive (Table 2-3). In other words, despite perceiving greater demand, participants in the loss condition were not inclined to increase effort to meet that demand.

We were also interested in the Frustration subscale, as the "positivity effect" view would make different predictions than the other two perspectives. That is, if older adults ignore or downplay negative information in the service of regulating emotion, they might be expected to show less frustration than young adults (especially in the loss condition) at the higher set sizes, when errors and thus losses are more likely. The "disengagement" perspective predicts a different chain of events: The feedback and loss information immediately after the trial is relatively difficult to ignore or avoid, and a resulting increase in frustration would be predicted to lead to subsequent, downstream disengagement. The "incentive increases motivation" viewpoint might also predict increased frustration, if that motivation or desire to achieve/retain reward is literally frustrated by the increase in errors, and thus losses, at higher set sizes (Angus & Harmon-Jones, 2019; Carver & Harmon-Jones, 2009).

For the Frustration subscale, set size had significant interactions with both incentive and age group. The 3-way interaction was not significant (Table 2-3). In both cases, the two groups (young vs old; loss vs control) were largely identical at the lower, easier, set sizes, with larger differences between the groups appearing at the higher, more difficult set sizes (Figure 2-2). Age group differences in particular closely paralleled the accuracy data in when they began to show a separation (i.e., older adults had low Frustration scores for set sizes 2-4 and began to show an increase around set size 5; whereas for young adults the sharper increase occurred around set size 6). In short, these data support the idea that the loss incentive increases frustration specifically at higher set sizes when errors are more likely to occur, and there is no evidence that older adults are either immune to or especially sensitive to this effect.

The other subscales were not as incisive theoretically, but are reported (Table 2-3, Supplemental Material S1 and S3) for completeness, including comparison with the prior study by Hess et al. (2016).

Figure 2-2. NASA-TLX Mental Demand, and Effort, and Frustration



Different colors/lines (control = black solid line, loss = red dashed line) and shapes (triangle = young adults (YA), circle = older adults (OA)) are used to highlight the different conditions. Error bars represent 95% confidence intervals. NASA-TLX: NASA Task Load Index

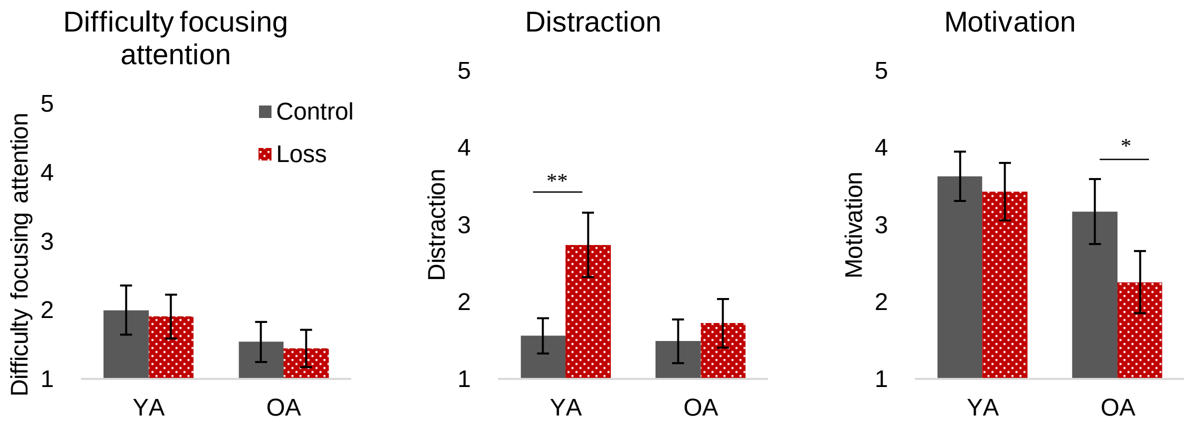
Loss incentives increase distraction in young adults and decrease motivation in older adults

Figure 2-3 shows the results of directly asking participants about their focus of attention, and the degree to which the feedback or incentive was distracting or motivating. Older adults gave lower ratings for difficulty focusing attention than did young adults, replicating counterintuitive but typical findings in the literature, $F(1, 160) = 8.47$, $p = .004$, $\eta_p^2 = .05$.

A significant Age × Incentive interactions for the distraction question indicated that young and older adults had different reactions to the loss incentive feedback, $F(1, 160) = 8.51$, $p = .004$, $\eta_p^2 = .049$. Young adults under loss incentive reported higher distraction than those in the control condition, $t(83) = -4.89$, $p < .001$, but this effect was not observed in older adults, $t(82) = -1.08$, $p = .285$. For the motivation question, we observed a significant incentive effect, $F(1, 160) = 8.25$, $p = .005$, $\eta_p^2 = .05$ where those under loss incentive show lower motivation. Although the Age × Incentive interaction was not significant, $F(1, 160) = 3.40$, $p = .067$, $\eta_p^2 = .02$, the incentive effect was largely driven by older adults, $t(82) = 3.08$, $p = .003$, and not significant for young adults, $t(83) = .80$, $p = .428$.

One caveat to these results is that they reflect participant's answers to the direct questions about their responses to the incentive and feedback. We did not see incentive effects on the more general measures provided by the IMI, including the Interest/Enjoyment scale (Supplemental Material S5). This may be due to the less targeted nature of the IMI questions and their focus on how fun, interesting, or enjoyable the task is rather than the participant's inner motivation or desire to do well.

Figure 2-3. State Attention and Motivation Questionnaire



*Different colors/patterns (control = black filled, loss = red dotted) are used to highlight the different conditions for young (YA) and older adults (OA). Error bars represent 95% confidence intervals. ** p < .001, * p < .01. Loss incentive increased distraction for young adults, decreased motivation for older adults.*

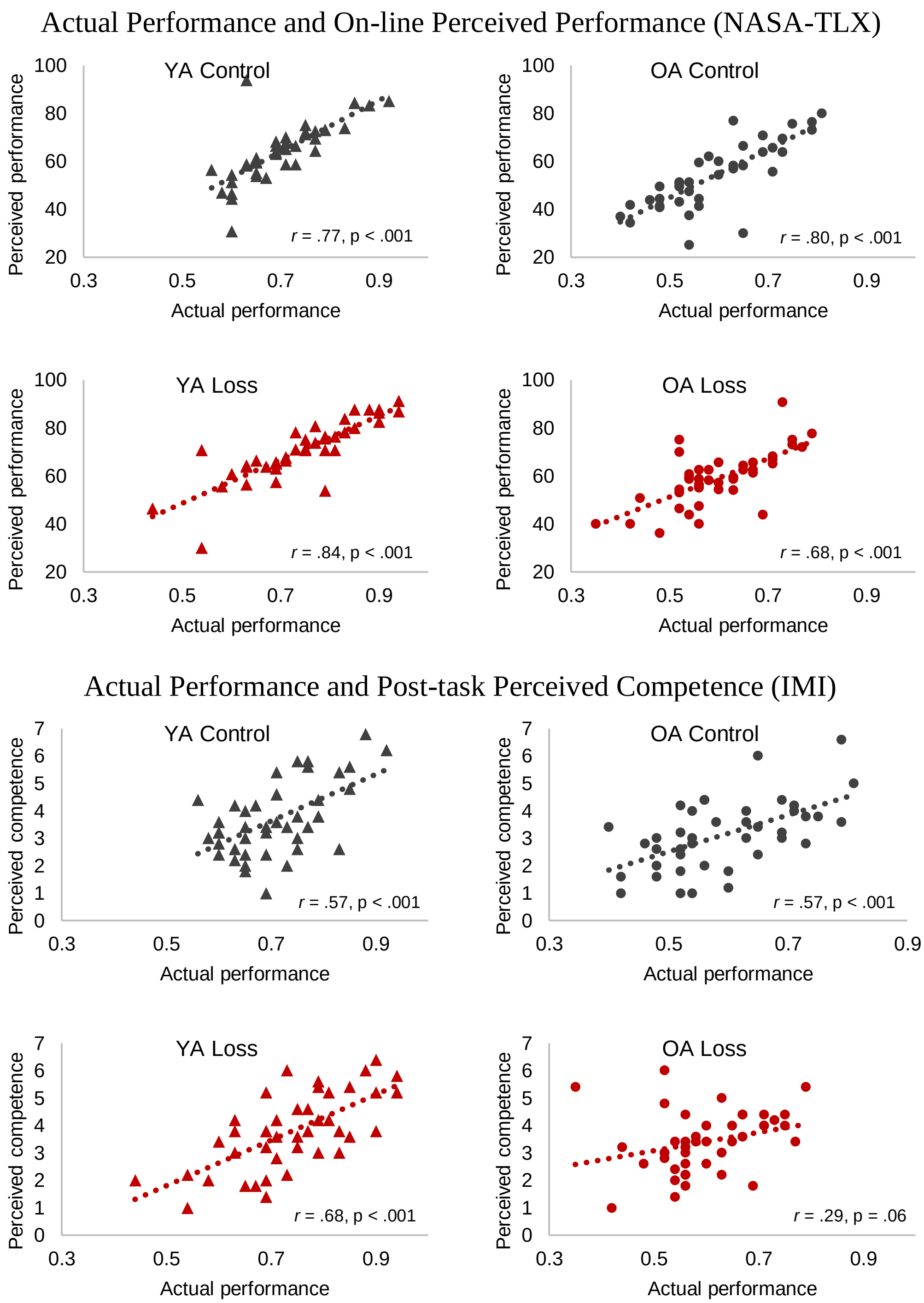
Loss incentives improve the accuracy of immediate, absolute metacognitive judgments, but may distort relative judgments of competence for older adults

We next conducted further exploratory analyses of how the loss incentive might affect participants' metacognitive judgments. The hypothesis that older adults ignore negative information predicts that older adults in the loss condition would have a weaker relationship between their actual and perceived (self-rated) performance. This was not the case for the Performance subscale of the NASA-TLX: Correlations between perceived and actual performance were moderately strong for all four groups (all $r \geq .68$ $p < .001$; Figure 2-4 top panel).

Moreover, the metacognitive difference scores (actual performance - self-rated performance) were analyzed using the same MLM design as used to analyze the NASA-TLX scales (see Supplemental Material S6 for the full results). The results showed that both younger and older adults in the loss condition in fact showed less discrepancy between their actual performance and perceived performance than did their counterparts in the control condition, $\beta = -4.84$, $t(165) = -2.43$, $p = .016$ (Figure 2-5). There was also a significant quadratic interaction between set size and incentive condition, $\beta = 0.45$, $t(1175) = 2.22$, $p = .026$. Both the control and loss groups tended to under-estimate their performance in the lower set sizes and get close to accurate judgement or slight over-estimation at the higher set sizes. The discrepancies between the groups appear to be greatest at the middle set sizes (SS4-7), where the loss incentive group's ratings underestimated their performance less than did those of the control group. Full MLM results for metacognitive difference scores are shown in Supplemental Material S6.

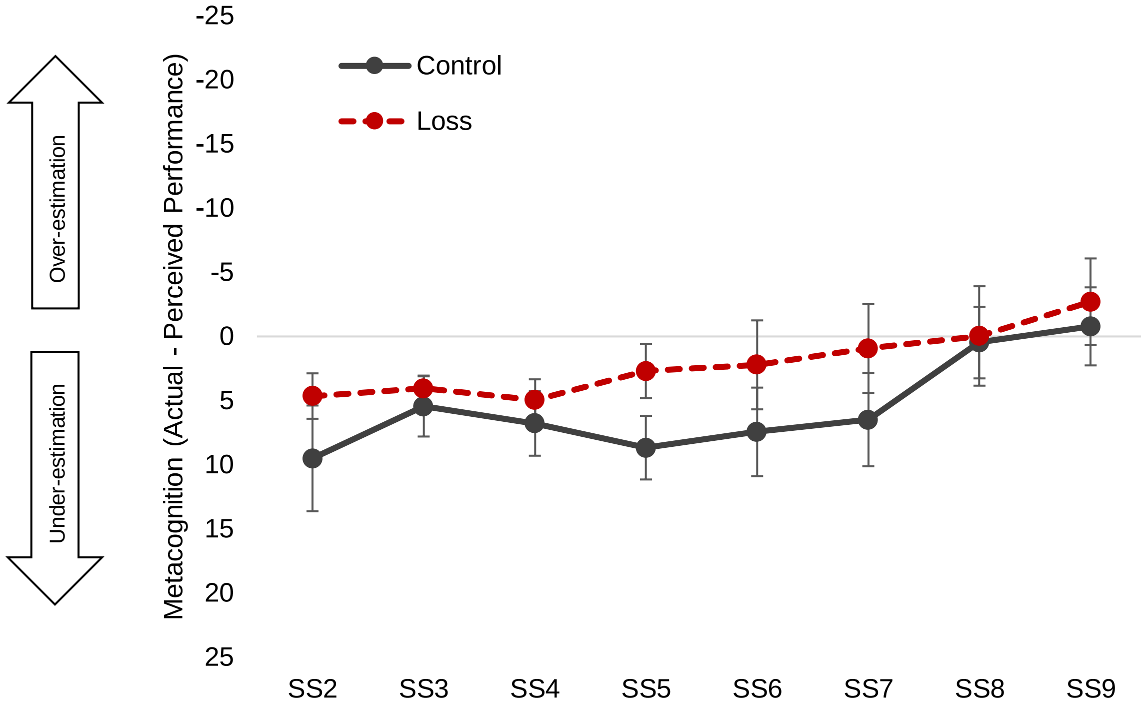
A different pattern emerged for the IMI Competence rating, which was given after the entire task (rather than immediately after run feedback) and focused on participants' overall satisfaction with their performance and whether they felt they had performed well in comparison with their peers. While the other 3 groups maintained moderate correlations between this measure and their actual performance, this correlation was only marginal for older adults in the loss condition, $r = .29$, $p = .061$ (Figure 2-4). This was significantly smaller than the correlation between their NASA-TLX Performance rating and actual performance (modified Fisher's z-test, $z = 2.37$, $p = .009$; Steiger, 1980; calculation tool provided by Lee & Preacher, 2013). For the other groups, the correlations between IMI Competence and actual performance remained in the moderate range, all $r \geq .57$, $p < .001$. Comparing across groups, Fisher's z tests showed that the correlation for older adults in the loss condition was significantly weaker than that of the young adults in the loss condition ($p = .009$), marginally so compared to the other two groups (both $p = .06$).

Figure 2-4. Relative metacognitive accuracy



Different colors (control = black, red = loss) and shapes (triangle = young adults (YA), circle = older adults (OA)) are used to highlight the different conditions. NASA-TLX: NASA Task Load Index, IMI: Intrinsic Motivation Inventory

Figure 2-5. Absolute metacognitive accuracy



Black solid line and red dashed line denote control and loss condition, respectively. Error bars represent 95% confidence intervals. Scale on y-axis is reversed for ease of interpretation. Zero means accurate judgement. See S7 for the full Age × Incentive graph. SS: Set size

Discussion

We examined the effects of a loss-based incentive on young and older adults' working memory performance, motivation, and metacognition. Incentive did not impact performance, but instead increased participants' perceptions of mental demand and their frustration at the higher, more demanding set sizes. The loss incentive also increased the absolute accuracy of immediate metacognitive judgments, that is, participants' ratings of how well they did compared to their actual performance. These results are not consistent either with the "incentive increases motivation" or the heuristic "older adults ignore loss information" hypotheses. Older adults were at least as sensitive to loss information in the immediate post-run ratings as were young adults, and their immediate post-run metacognitive performance ratings were particularly accurate in the loss condition, suggesting close attention to the loss incentive feedback.

The results did not completely fit any of the predictions outlined in Table 2-2. An overview of the predictions from each of the theoretical perspectives, but overall seemed most consistent with the idea that, especially at the highest set sizes when errors were most common, loss incentive increased the perceived "costs" (mental demand, frustration) of performance. Somewhat contrary to the suggestion that older adults may be more sensitive to unavoidable negative information and/or more sensitive to such costs (c.f., Charles, 2010; Hess, 2014), the effects appeared to be of similar size for younger and older adults. However, other aspects of the results suggest that these equivalent effects occurred for different reasons, with the loss incentive being more distracting to young adults, more de-motivating to older adults. The change in metacognitive accuracy by older adults in the loss condition from immediate, specific performance judgments versus later judgements of competency in the task as a whole also seems consistent with the suggestion that when negative information is unavoidable in the moment, older adults may instead cope by reframing later on (Charles, 2010).

Despite their increased perception of demand and frustration, as well as more accurate judgements of performance, participants in the loss condition did not increase their effort to meet that demand and improve their performance. To further explore the possibility that for older adults, this failure to increase effort might be related to disengagement and decreased motivation, we conducted additional exploratory analyses examining correlations between changes on the NASA-TLX Effort scale from the lowest (2) to highest (9) set size, and the post-task question about motivation (p-values corrected for multiple comparisons using the false discovery rate (FDR) approach because of the exploratory nature of the analyses). The relationship between effort and motivation change went in the opposite direction for older adults in the control and loss conditions, Fisher's $z = 2.12$, $p = .034$. However, this result should be considered only suggestive and interpreted with caution given the exploratory nature of the analyses and that the individual correlations did not reach significance (Kendall rank correlation coefficient for control condition: *tau* = .22, $p_{FDR} = .14$; loss condition: *tau* = -.25, $p_{FDR} = .14$). The loss-reversal pattern appears to be specific to older adults, and to the motivation measure: Correlations for young adults did not approach significance (all $p_{FDR} > .40$), and the older adult the control and loss incentive groups showed similar correlations between distraction ratings and increases in effort (control *tau* = -.38, $p_{FDR} = .006$; loss *tau* = -.26, $p_{FDR} = 0.034$).

In addition, although it had not been part of our thought process in setting up the correlation matrix, we also observed that for the control groups, motivation and distraction tended to be negatively correlated (*tau* = -.35, $p_{FDR} = .021$ for young adults; *tau* = -.25, $p_{FDR} = .07$ for older adults) with the opposite pattern in the loss groups (*tau* = .23, $p_{FDR} = .07$ for young adults; tau = .55, p_{FDR} < .001 for older adults). This again seems inconsistent with the idea that older adults ignored the negative loss incentive information. Instead, for both age groups, the more motivated they were by the loss incentive information, the more distracting they found it.

Performance vs. subjective measures

Contrary to initial expectations, we did not see either beneficial or detrimental effects on performance by either group. Figure 2-1 suggests a very small numerical advantage for the loss condition, but even at the set size with the largest difference the effect is quite small (d = .24). We originally chose this task because Hess et al. (2016) had found age and set size differences in a physiological measure of engagement during the task. An earlier set of studies in our lab found that loss incentive reduced older adults' performance on a measure of focused attention and increased their self-reported mind-wandering (Lin, 2018; Lin et al., 2019) and so we had thought we might see similar effects here.

Of course, it's possible that our loss incentive manipulation was simply ineffective and inadequate. A reviewer raised the question of whether this might be the case because of the between-subjects design, and whether a within-session contrast with reward or neutral trials might be necessary to make the loss salient produce an effect. Although that explanation cannot be ruled out, we think it is unlikely to be the case. First, there are the findings of effects on the subjective measures, suggesting that the loss incentive was indeed salient, and that the lack of effects on working memory performance were due to a lack of sensitivity in the measure. Other studies suggest that between-subjects incentive manipulations can affect performance in older adults: Barber and Mather found crossover interactions for between-subjects manipulations of stereotype threat and gain/loss incentive on both working memory and clinical cognitive assessments (Barber et al., 2015; Barber & Mather, 2013). As we have already noted, other datasets from our lab show that older adults' performance can be impaired by similar between-subjects incentive manipulations.

Instead, although targeted experiments will be required to test it, our working hypothesis is that discrepancies across studies in whether they show performance differences as a result of incentive, especially loss incentive, may be heavily influenced by differences in the task constraints and proactive control requirements. Incentives appear to largely affect the engagement of proactive control (Chiew & Braver, 2016; Mäki-Marttunen, Hagen, & Espeseth, 2019; general reductions in response time may be an exception). The focused-attention task used in our earlier study made strong demands on self-initiated, proactive processing (rare targets and responses, low-salience targets distinguishable only by their duration). The LNS task uses a relatively fast presentation of to-be-remembered stimuli (one per second) and requires a verbal response on each trial – literally requiring the participant to 'engage with' the experimenter. Thus, it may rely more on reactive control; the low ratings of mind-wandering and difficulty focusing attention seem consistent with that interpretation. Future experiments that specifically isolate task constraints and top-down control requirements will be needed to determine the plausibility of this interpretation.

On the other hand, the lack of performance differences helps to alleviate concerns that the effects we see on the subjective measures are simply downstream artifacts of poor performance. That is, it is difficult to say that the higher mental demand ratings (for example) by participants in the loss condition are simply an attempt to 'excuse' lower performance, since they did not in fact have lower performance.

We also examined whether the end-of-task measures might be especially influenced by the last few runs. This was the case for the IMI competence measure, as might be expected, given that the final runs are also the ones where performance is most difficult and competence becomes a question: For all groups except the older adult loss group, correlations between performance and the IMI Competence ratings were higher for the last 3 set sizes (r = .36 - .60) than for the first 3 set sizes (r = -.31 - .31). For the older adult loss group, correlations were consistently low (r = -.06 - .17 for the first 3 set sizes; r = .07 - .27 for the last set sizes), as would be expected from the results shown in Figure 2-4. There were no systematic changes in correlation with set size for the SAMQ Motivation or Distraction questions, or IMI Interest/Enjoyment measures, especially for the incentive groups. (The young adult control group showed hints of such a pattern for the IMI Interest/Enjoyment measure (r = -.06 - .28 for the first 3 set sizes; r = .13 -. 36 for the last 3); but given fluctuations across the set sizes this seems unlikely to be meaningful.) Thus, there is no evidence that the end-of-task measures of motivation and distraction were unduly influenced by the last few runs/highest set sizes.

The opposite critique may come to mind when considering age differences: Young adults had better performance than older adults. Of course, that is also the case in most previous studies of age × incentive interactions in cognitive control tasks. The present task has the advantage that the range of set sizes used here allows us to examine the issue, at least for the post-run NASA-TLX ratings. We did a follow-up analysis using only those set sizes where performance for young and older adults was equivalent (between 25% - 75% accuracy; set sizes 5-7 for older adults; set sizes 6-8 for young adults; rescaled as “low, medium and high” for each group). In that case the Mental Demand and Effort ratings were generally higher for young adults, whereas Frustration remained somewhat higher for older adults. It did not introduce any new age ×

incentive interactions compared to the analyses reported above, although there was a trend for the Effort ratings of older adults in the loss condition to be especially low. In general, comparing the restricted-range results to the full dataset suggests that incentive effects overall were greatest at the highest set sizes, when load exceeded capacity, but there was no suggestion of interactions with age or that age differences in performance played a role.

Limitations and comparisons (or the lack thereof) with previous studies

There are several limitations and differences from other studies that should be kept in mind when interpreting these results and their place in the literature, as well as strengths and weaknesses that are shared with other studies in this field. First, we focused on loss incentives, because they are understudied, losses are thought to be increasingly important in later life (Baltes et al., 1999), the opportunity to avoid losses is often used to motivate older adults, and this is the condition that is most theoretically incisive: The general/intuitive "incentive increases motivation and thus attention and performance", heuristic positivity effect ("older adults ignore negative information") and nuanced positivity effect/disengagement hypothesis all make similar predictions for reward conditions. The "incentive as cognitive load" makes similar predictions for reward and loss incentive. Prior studies that did examine both reward and loss effects on cognitive performance in young and older adults have already found patterns contradicting the "motivational shift" hypothesis, which appears to apply to more general orientations and choice behaviors, and possibly to avoidance learning.

It is the case that we cannot rule out that "gain" incentives would have had similar results in the present study; the complementary criticism applies to the majority of studies that have focused solely on gain incentives. Behavioral (O'Brien & Hess, 2019) and neural (e.g., Cubillo et al., 2019; Paschke et al., 2015) evidence suggests that gain and loss operate through partially independent processes. However, this issue needs further examination, and in general, studies in this field would benefit from including both conditions. What we can say is that we did not find any evidence that loss incentive generally improved performance and motivation, and that older adults appeared to be at least as responsive to the loss incentive as were young adults.

Second, as stated earlier, it was explicitly *not* our intention to do another incremental variation on existing studies that, besides focusing on gain effects, have with rare exception used trial-wise manipulations on cognitive control tasks. We instead wanted to take the first step in addressing several important but understudied questions, not only of incentive type (loss, as noted above), but also of cognitive domain (working memory) and session-wide implementation of incentives. While the differences in our approach make it difficult to compare our results directly to existing laboratory studies, we believe that this last aspect is especially important, given how performance incentives are typically implemented in everyday life. Trial-wise implementations have an advantage in statistical power, but this may come at the cost of generalization to real-world situations (c.f., Cerasoli, Nicklin, & Ford, 2014; Deci, Koestner, & Ryan, 1999).

Another reason we have specifically avoided trial-by-trial incentives in our studies is that the changing incentive cues and delivery of reward/loss information on every or almost every trial are likely to drive attention and engagement in the "bottom-up" fashion described earlier. Several studies have already found different incentive effects for block- or run-wise implementation of incentives versus trial-wise manipulations (Bruening et al., 2018; Jimura et al., 2010; Paschke et al., 2015); differences from session-wide effects may be even more pronounced (Lin, 2018). Although they examined downstream effects of correct/error and gain/loss feedback on incidental encoding during a previous task rather than incentivized performance, analysis by Mather and Schoeke (2011) suggest that trial-history effects could be an interesting compromise method to test whether, e.g., disengagement (or overarousal) builds up over multiple errors or losses (see also Schmitt et al., 2017). Regardless, it seems important to have both types of studies in the literature to see where effects converge or diverge, and in the latter case to ultimately conduct targeted, parametric manipulations to understand why.

Third, our use of subjective response measures, especially examination of potential effects on metacognition, is relatively novel and provides further insights into the pathways by which incentives may have their effects. However, such measures come with their own limitations, including potential response bias, impression management, and so on. As noted above, although the lack of incentive effects on performance can be seen as a limitation in some respects, raising questions about whether the incentive manipulation was effective, on the other hand, has the advantage of alleviating the concerns that the loss groups' higher ratings of mental demand, frustration, and distraction (young adults) or reduced motivation (older adults) might be attempts to blame poor performance on those factors in retrospect. Besides their preserved actual performance, participants in the loss condition also gave themselves higher and more accurate immediate self-ratings of performance, especially at the higher set sizes. It seems hard to reconcile this greater confidence and accuracy with the idea that they were more likely to use increased mental demand, frustration, distraction, or loss of motivation to excuse performance declines. Again, what we have here is a complementary set of advantages and disadvantages compared to studies that have examined physiological or neural responses to incentive manipulations; what is ultimately needed is a combined approach.

Another critique that can be applied to this study and almost every other study of age × incentive effects is “maybe older adults just don’t care (as much) about the money”. This seems a bit hard to reconcile with the equivalent effects of the incentive on young and older adults for many of our measures. However – although it should be considered exploratory – the different patterns shown by young and older adults for the post-task distraction vs. motivation questions suggests that there may be at least some truth to this. In a larger sense, we agree entirely that older adults, at least those who are likely to participate in studies in our lab and the labs of other university-based investigators, are unlikely to find the money per se of primary interest. We suspect that instead the loss incentive in particular has its power by drawing attention to errors. We are beginning studies to test this possibility more directly. Providing some indirect support, Dhingra et al. (2020) reported less behavioral and neural sensitivity to incentive magnitude (dollar vs. cent) in older vs. young adults. However, in the case of losses, this was due to a relatively higher response to even small losses in older adults. Another important question for this area of study more generally is how different incentive amounts and types may affect results, and potentially interact with participant demographics.

Finally, an aspect of the present study lacking in many others was our examination of subjective measures, both immediately and post-task. It is interesting that younger and older adults showed similar incentive effects for the ratings of mental demand, performance, and frustration taken during the task, with age differences emerging in the more holistic, post-task measures. This could be seen as consistent with claims that older adults may be just as affected as young adults by unavoidable negative information “in the moment”, but more likely to respond to it with more passive strategies, and by later reframing or reappraising the situation to put it in a more positive light (e.g., Charles, 2010). Future studies using instruments designed to more systematically explore how metacognition and the emotional/motivational response to incentives is affected by the specificity (atomistic vs holistic) and temporal (during/immediately after performance vs somewhat later on) dimensions, as well as their interaction, will be important for more definitively identifying which factors exert a critical influence over these effects.

What are the roles of "engagement" and task constraints in studies of incentive?

As noted in the Introduction, incentives are often used (or assumed) to increase proactive control in an effort to improve performance (Botvinick & Braver, 2015); the "engagement" idea of Hess and colleagues (Ennis et al., 2014; Hess, 2014) is similar. This leads to the question of how to define "engagement". Although Hess's theoretical writings have not specifically addressed issues of top-down (proactive, goal-related) vs. bottom-up (reactive, task or stimulus related) factors, he has noted that he means the term to be synonymous with "effort" and emphasizes the idea of the choice whether or not to engage, which seems more consistent with the top-down interpretation. However, the degree to which engagement of this type is required likely varies inversely with the degree to which the task itself is inherently "engaging" because of constraints or stimuli that drive attention in a more bottom-up or reactive fashion. Several fMRI studies indicate that incentives may have their primary effects on proactive, self-initiated control (e.g., whether participants engage frontoparietal regions at the point of a cue which would allow them to prepare for the upcoming probe vs. waiting for the probe), though this has primarily been demonstrated for reward incentives (e.g., Etzel, Cole, Zacks, Kay, & Braver, 2015; Jimura, Locke, & Braver, 2010; see Cubillo, Makwana, & Hare, 2019 for effects of loss incentives suggesting a shift to reactive control.).

Putting this together with the boundary conditions on the positivity effect noted by Carstensen and colleagues, when loss information is unavoidable but task constraints are high, older adults may react to the negative information at a subjective and motivational-emotional level without this drop in motivational "engagement" decreasing performance. One interesting prediction is that higher task constraints should lead to preserved performance at the cost of greater subjective demand and frustration, whereas relatively unconstrained tasks provide an opportunity to reduce engagement and negative subjective experience, but at the cost of reduced performance. This hypothesis regarding the potential role of task constraints should be regarded as that – a hypothesis – rather than a definitive conclusion.

An alternative, less process-specific explanation for the differences between the studies might be that the present task was simply more difficult, especially at the higher set sizes. However, this alternative runs into some complications given that on the one hand more difficult tasks typically decreases mind-wandering (e.g., Baird et al., 2012; Konishi, McLaren, Engen, & Smallwood, 2015; see Seli, Konishi, Risko, & Smilek, 2018 for discussion of exceptions), but on the other hand are usually considered to be exactly the situations in which incentive and motivation are likely to be most important (e.g., Botvinick & Braver, 2015; Ferdinand & Czernochowski, 2018; Kostandyan et al., 2019).

To our knowledge, there has not been a systematic investigation of how either incentive effects or the positivity effect may be impacted by changing the degree to which engagement is driven by bottom-up vs. top-down within the same task. One way to differentiate these ideas while controlling for task difficulty might be, e.g., comparing rare-response versus frequent-response versions of the same attention task (c.f., Staub, Doignon-Camus, Marques-Carneiro, Bacon, & Bonnefond, 2015), or varying retention intervals in a working-memory task. The latter idea was tested in Chapter 3 (Study 2) of the current dissertation. This kind of task analysis and testing of parameters and boundary conditions may be an important direction for future research, especially as many real-world tasks are relatively unconstrained (e.g., reading, writing, participating in a conversation, driving) and thus may rely more on the top-down, self-initiated aspects of attention (Hess et al., 2011, 2018).

Summary and conclusions

The study of age differences in the response to incentives during cognitive challenging tasks is still at very early stages, though growing quickly. Thus far most studies have used attention and cognitive control tasks, used reward incentives, and implemented incentive on a trial-wise basis. We took a complementary approach (working memory task, loss incentive, session-wide incentive implementation), with a complementary set of strengths and weaknesses in our methods, design, and the conclusions that can be drawn.

Our results suggest caution in generalizing the results of previous studies, especially to everyday life scenarios: They do not support the idea that incentive generally (i.e., regardless of valence) increases motivation and performance even for young adults, or that older adults ignore negative information provided by loss incentives. Another relatively novel aspect of our study was the inclusion of metacognitive and self-report measures of motivation, distraction, and related constructs. The loss incentive appeared to increase participants' attention to their own performance, their perceptions of mental demand at higher set sizes, and their frustration at not being able to maintain good performance at those higher set sizes. Interestingly, these perceived increases in demand and frustration at higher set sizes were not met with concomitant increases in effort. Instead, young adults reported finding the incentive distracting, whereas older adults found it demotivating.

These results come with the usual caveats accompanying self-report measures, though supposedly more objective physiological measures have a complementary problem of somewhat subjective interpretation by the investigator (as opposed to the participant). That is, they are often related to some aspect of sympathetic arousal, but is this arousal indexing engagement or some other construct such as frustration or anxiety? Ideally future studies will combine these approaches; self-report measures may provide richer and more precise interpretations of the neural and physiological results, especially if combined with fine-grained analysis of performance results (e.g., response time, vigor (speed or force), or variability) and careful experiment construction to get at different cognitive, emotional, or motivational constructs. The role of individual and cultural differences in attitudes towards different types and levels of incentives is also an understudied topic. Finally, task constraints vs. the demand for proactive, self-initiated top-down control may be an important but as yet somewhat understudied factor in determining when and how incentives may affect performance and/or subjective responses.

In short, our study may raise as many questions as it answers. One of the most important questions it raises concerns the degree to which the results of previous studies can be generalized, especially to real-world scenarios. However, we believe that in the long run a careful consideration of issues related to proactive, top-down control versus reactive, bottom-up attention will provide an important organizing principle for understanding the literature and driving it forward.

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Supplemental Material

The Supplemental Material for this chapter can be found online at: https://osf.io/tjm4h/

Chapter 3 Opposite Reactions to Loss Incentive by Young and Older Adults: Insights From Diffusion Modeling

Introduction

Everyday life imposes demands on working memory that can be especially challenging and costly to older adults. Failing to process all the information involved in an important Zoom meeting, financial decision, or busy traffic intersection could cost you your job, your independence, or even your life. Different theoretical perspectives make different predictions as to how loss-based incentives might affect working memory in young and older adults, but there has been little direct investigation. The present study takes a step towards addressing this gap. Moreover, manipulation of task parameters, diffusion modeling analyses, and self-report measures are used to specify which aspects of cognitive-motivational processing are affected.

Theoretical perspectives on cognition-motivation interactions in aging are relatively consistent in predicting that gain incentives will improve older adults' motivation and performance (though possibly to a lesser degree compared to young adults), but vary considerably in their predictions on loss effects. The popular idea that older adults are more loss-averse (but see Mikels & Reed, 2009; O'Brien & Hess, 2020) suggests that they should be more motivated to avoid losses. A similar prediction is made by motivation-shift theory, which builds on the observation that losses become more prevalent in later life. Moreover, pursuing gains often involves investment of (cognitive, energetic, temporal, etc.) resources differentially limited for older adults. Thus, motivation-shift theory proposes that while young adults are more motivated to achieve gains, older adults are more motivated to avoid losses (Best & Freund, 2018; Freund & Ebner, 2005). However, while motivation-shift theory may help explain older adults' preferences and choices in some situations (Byrne & Ghaiumy Anaraky, 2020; Ebner et al., 2006; Frank & Kong, 2008), there is little evidence that loss incentives differentially improve older adults' performance.

Instead, several studies of loss incentive effects on cognitive tasks, especially those measuring proactive control or executive attention, suggest that older adults are less sensitive to loss incentives (e.g., Bagurdes et al., 2008; Di Rosa et al., 2015; Pachur et al., 2017; Williams et al., 2017, 2018). These results parallel those seen in the reinforcement-learning literature (see review by Samanez-Larkin & Knutson, 2015), and likewise have typically been interpreted in terms of the age-related positivity effect: The tendency of older adults to direct attention and memory away from negative information, presumably in the service of maintaining a positive emotional state. This interpretation would predict that older adults should be less responsive to loss incentive than are young adults. However, as we describe further below, the positivity effect may not apply when negative information is personally relevant (English & Carstensen, 2015; Tomaszczyk et al., 2008) as it presumably would be for errors.

The third possibility – that loss incentive will reduce older adults' motivation and performance – is suggested by studies of real world cognition. For example, higher anxiety about health or financial concerns in older adults leads to less information-seeking about those topics, and impaired processing of related information (e.g., Kiso & Hershey, 2017; Persoskie et al., 2014). Likewise, older adults' perception of the effectiveness of health messaging is more impacted by the degree of positive emotion elicited by gain framing, whereas young adults' perception is more influenced by the negative emotion elicited by loss framing (Liu et al., 2019).

Older workers have stronger negative emotional reactions to making an error while working with computers, and are less likely than younger workers to self-initiate steps to solve the problem (Birdi & Zapf, 1997). Loss incentives reduce older adults' performance on a common dementia screening test (Word List Memory from the CERAD; Barber et al., 2015).

There are multiple potential mechanisms for loss-induced performance impairments in older adults. First, older adults may be more upset and disrupted by errors, which are made more salient by losses incurred by making those errors. Although the positivity effect suggests that older adults ignore negative information, the major theory behind the positivity effect describes it as a goal-directed process (see reviews by Reed & Carstensen, 2012; see Barber et al., 2020; Carstensen & DeLiema, 2018 for discussion of overlaps and distinctions from strategic processes). When negative information is especially salient or self-relevant, older adults often pay more attention to it than do young adults, and may even be more vulnerable to its disruptive effects (see Charles, 2010 for review and theoretical framework; see Barber, 2020 for applied examples in driving, employment, and dementia assessment).

Alternatively, loss incentives may de-motivate older adults and lead them to disengage from the task itself – possibly as a form of self-handicapping and to reduce emotional threat, or because loss incentives increase the subjective costs of task engagement (see Hess, 2014 for a related view).[2] A third proposal is that incentives, especially loss incentives, impose distraction or cognitive load especially detrimental to older adults (Ferdinand & Czernochowski, 2018; Schmitt et al., 2017).

[2] The term "engagement" has been used in different ways across the literature. We use "engage" in the Oxford dictionary sense: "to occupy, attract, or involve" attention and cognitive processing. Engagement may be driven to various degrees by effortful (aka top-down, goal driven, self-initiated, proactive) and automatic (bottom-up, stimulus driven, reactive) processes. We use the term "constraint" in a manner similar to Craik's "environmental support" (Craik & Byrd, 1982): A high constraint task is one that has features (e.g., salient stimuli, frequent cues) that drive engagement in a exogenous, bottom-up fashion; a low-constraint task relies more on self-initiation.

The discrepant findings of laboratory vs. real-world studies may be at least partially due to differences in task and incentive structure. The tasks used in most age × incentive laboratory studies (e.g., Attention Network Test, flanker, AX-CPT) have features that help constrain attention and engagement: perceptually distinct targets, fast-paced trials, and frequent responses. These constraints may help keep participants on-task and performing relatively well even when motivation is low. In contrast, everyday cognitive tasks (e.g., cooking a meal, driving, planning an employee work schedule) often lack these constraining features. This lack of constraint may make everyday tasks more reliant on self-initiation, and thus more sensitive to drops in motivation.

Laboratory and real-world situations also differ in how incentives are typically presented and implemented. Most laboratory studies borrow the structure used in reinforcement-learning studies: trial-wise randomization of incentive conditions, with a cue at the start of each trial informing subjects of its value. Such frequent cues may continuously draw attention back to the task despite low motivation. Real-world incentives typically apply to an entire session of performance, or even beyond. Whether you are taking a driving exam, doing your taxes, or solving a complicated problem at work, gains for successful performance and losses for failure typically apply to the final outcome, rather than each step assigned a random cue indicating potential loss or reward.

The intermixed, randomized implementation of incentive used in most laboratory studies may also create problems for interpretation. Putatively neutral control trials are responded to differently if they are presented in the context of gains vs. losses (i.e., a “nongain” elicits a different subjective response than a “nonloss”; Idson et al., 2000); and if gain and loss trials are intermixed a gain is a nonloss and vice versa. Moreover, incentives are often thought to increase proactive control, but older adults do not adjust their level of control as dynamically as do young adults, even in non-incentivized tasks (Braver et al., 2001; see Bowen et al., 2020 for related evidence from a memory paradigm). Therefore, when older adults show smaller performance changes in response to changing incentive than do young adults, it may be difficult to disentangle whether this represents reduced sensitivity to the incentive per se versus a more general age-related impairment in dynamically modulating control. Thurm et al., (2018) noted that older adults' failure to adjust response bias in accordance with trial-wise changes in reward in their study might reflect difficulties in adapting to changing reward context. Even young adults can show large carryover effects: The response to a non-incentivized trial is quite different depending on whether it occurs intermixed with incentivized trials or in a block of non-incentivized trials (e.g., Jimura et al., 2010; see Schmitt et al., 2017 for differential effects in older adutls). Differences between intermixed trials and between-subjects manipulations are likely even larger.

To our knowledge, only two previous studies have examined loss effects on working memory performance in older adults (see Thurm et al., 2018; Manga et al., 2020 for gain-effect studies). Both used a between-subjects incentive manipulation, but with relatively high-constraint tasks: Barber & Mather (2013) used a sentence span task that required participants to verify the meaningfulness of each sentence via button press, remember the sentence-final word, and then at the end of the set, recite those sentence-final words to the experimenter. Both the button-press and the recitation of the words to the experimenter would require the participant to actively engage with the task, and they did not find differential effects of gain or loss unless a stereotype-threat manipulation was also introduced (there was no young adult comparison group). Study 1 (Chapter 2; Jang et al., 2020) in the current dissertation used a letter-number sequencing task in which the experimenter spoke a random series of letters and numbers to the participant, who was then asked to immediately repeat them back in alphanumeric order – again actively engaging with the task (and experimenter) on every trial. The loss incentive reduced older adults' subjective motivation, but not performance. The lack of performance effects in this working memory task, despite the drop in subjective motivation, contrasted with older adults' loss-induced performance impairments during a low-constraint attention task (slow-paced, rare targets identifiable only by different duration; Lin et al., 2019).

We hypothesized that a working memory task with relatively low constraints, similar to real-world situations requiring self-initiated processing, would show loss-related performance impairments in older adults (see discussion in Study 1 and Jang et al., 2020). The Sternberg working memory task presents a set of memoranda, followed by a retention interval and then a probe which the participant must identify as either being a member of the memory set or a new, unstudied item. It thus implements a scaled-down simulation of many real-world situations that require holding information in mind for a short period of time, e.g., remembering whether it's a teaspoon or a tablespoon as we look away from the cookbook to our ingredients, remembering the next turn in our directions long enough to recognize the appropriate street sign. Although a response is required to each probe item, attention and engagement during the encoding and retention period rely on self-initiation.

As an additional test of the possibility that task constraints determine whether older adults show loss-related performance impairments, we manipulated retention interval. Our logic was that the longer retention interval presented a lower-constraint situation, with greater opportunity to disengage from the task, and thus might be more sensitive to incentive effects. The longer retention interval was predicted to lead to greater incentive-related improvements for young adults, and larger performance reductions for older adults. Of secondary interest, the Sternberg task allows an independent manipulation of load (number of items in the memory set), allowing us to test the alternative proposal that loss incentive increases cognitive load (Ferdinand & Czernochowski, 2018; Schmitt et al., 2017). If so, loss-induced performance reductions for older adults might be especially pronounced at higher set sizes.

Our primary hypothesis was that loss incentive would have opposite quantitative effects on motivation, engagement, and performance for young vs older adults. There may also be important qualitative age differences in which processes are affected, and how. For example, older adults often put more emphasis on accuracy than speed compared to young adults; incentives can either reduce or exaggerate these differences (Di Rosa et al., 2015; Touron & Hertzog, 2009; Williams et al., 2018). Likewise, in recognition memory situations, including probe-recognition working memory tasks like the one used here, older adults often show a liberal bias – i.e., a bias towards incorrectly saying that unstudied items were members of the memory set (Huh et al., 2006). To our knowledge, the Thurm et al., (2018) study is the only incentive-working memory study to examine potential age differences in incentive effects on bias; young but not older adults showed increased conservatism in response to gain incentive (see also young adult data in Massar et al., 2020). As noted earlier, this study used a trial-wise incentive manipulation and the authors speculated that the lack of incentive effects for older adults could reflect difficulties in switching reward context.

To examine how loss incentive affected different processing components, we used diffusion modeling to estimate parameters related to the quality of the memory representation (drift rate), speed-accuracy tradeoffs (boundary separation), response bias, and nondecision factors (see Greene & Rhodes, 2020, for discussion of the advantages of this modeling approach for understanding cognitive aging). Our main hypothesis was that if the incentive affected task engagement, it should have its primary effects on drift rate, as motivation might affect attention to and quality of encoding and maintenance. Alternatively, it could affect decision bias – for example, if older adults' liberal decision bias under normal circumstances reflects motivation to demonstrate "good memory" – or the nondecision component, if it has a general effect on increasing or decreasing arousal and thus motor speed.

We included subjective measures of motivation, distraction, and mental workload to inform interpretation of the performance and diffusion-modeling results. Our main prediction was that the loss incentive would increase motivation for young adults, but decrease it for older adults. We did not expect to find incentive effects on measures more closely related to perceived mental demand, effort, frustration, and similar constructs, as the relatively open-ended nature of the working memory task used here allows participants to adjust their level of effort according to their level of motivation (see Jang et al., 2020 for earlier discussion of this hypothesis and Zhang et al., 2021 for related data; Massar et al., 2020 for evidence that task parameters may determine whether performance and subjective measures align).

To summarize, the present study begins to test competing theories and address existing knowledge gaps about age differences in the effects of loss incentive on working memory. Based on the literature and previous experiments from our own lab, we hypothesized that loss incentive will increase the motivation and performance of young adults, with opposite effects for older adults. We manipulated task parameters (retention interval, set size) and used diffusion modeling to identify which of several possible mechanisms (engagement, cognitive load, strategic biases, arousal) might underlie incentive effects, and whether those there the same for both age groups. Finally, self-report measures assessed participants' subjective experience and constrained interpretation of the performance and modeling results.

To preview our results, we found that the loss incentive had opposite effects on performance and self-reported motivation in younger versus older adults. The diffusion modeling results suggested drift rate, a proxy for the quality of the memory representation, as the primary locus of these effects. Contrary to our expectations, the effects of the incentive were not magnified with longer retention intervals. Both age groups counterintuitively performed better and had higher drift rates with longer retention intervals, regardless of incentive. More detailed analyses revealed that these effects were specific to the correct rejection of unstudied probes. These latter findings, while exploratory, may help clarify the role of time in working memory.

Method

Participants

Sixty-five (50 female) young adults and 51 (32 female) older adults recruited from the University of Michigan and the surrounding community were included in the analysis. See Table 3-1 for demographics, Supplemental Material S15 for exclusion data; S23 for description of sample-size determination and power estimates. Participants were screened to ensure physical and psychological health with no history of anxiety, depression, attention deficit hyperactivity disorder (ADHD), or head injury, and no use of medications that could affect cognition. The Extended Range Vocabulary Test Version 3 (ERVT; Ekstrom, 1976) was used as a screen for participants who might not understand the instructions or were generally unmotivated; a minimum score of 9 out of a possible 48 was required. For older adults, a Mini Mental State Examination score (MMSE; Folstein et al., 1983) of 27 or greater was required. Young and older adults received $10 and $12 per hour respectively for their participation. The study was approved by the University of Michigan Institutional Review Board.

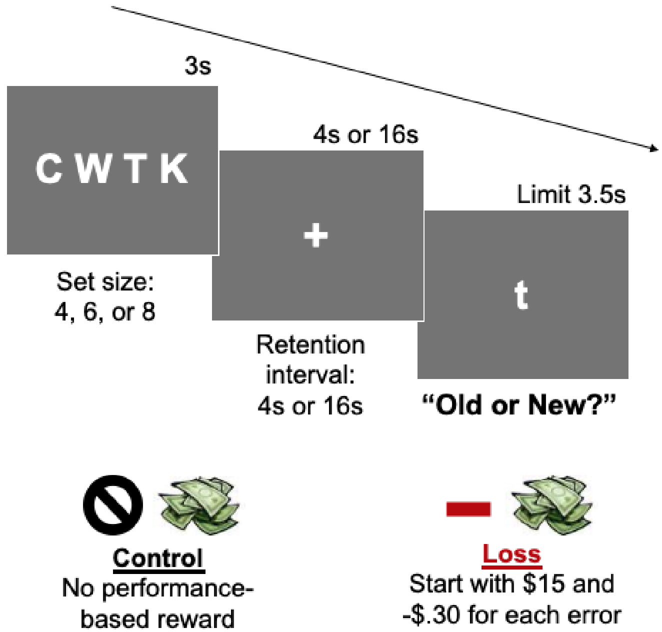
Design

Age group (young, older adults) and incentive condition (control, loss incentive) were the group-level, between-subjects variables of primary interest; set size (4, 6, 8 letters) and retention interval (4, 16 seconds) were within-subjects variables of secondary interest. Participants within each age group were randomly assigned to the control or loss incentive condition.

Working Memory Task

A Sternberg-type probe recognition task was used to measure working memory (Figure 3-1). The task was programed using PsychoPy version 3 (Peirce, 2007). Each trial began with a 3-second presentation of the memory set (4, 6, or 8 letters, varied randomly across trials). A fixation cross was then presented during the retention interval (4 or 16 seconds, varied randomly across trials). Then a lower-case letter appeared in the center of the screen, and participants pressed the “z” or “/” key to indicate whether the letter was/was not in the memory set (response key assignment counterbalanced across participants). There was a 3.5 seconds response time limit for making a response; if no response was made within this limit, the trial was considered incorrect. After each trial, participants were given performance feedback (trial-level accuracy and run-level percent correct/incorrect). Participants completed 5 runs, 30 trials each (total 150 trials).

Figure 3-1. Sternberg working memory task and incentive conditions



On each trial, participants viewed a set of letters, followed by a retention interval or 4 or 16 seconds (within subjects). They were then presented with a probe item and asked to indicate if it was (old) or was not (new) a member of the memory set. Incentive (control or loss) was implemented between subjects; see Method for details.

Questionnaires

Questionnaires were self-administered after the instructions were provided by the experimenter and the participants were given the chance to ask questions.

Poor Attentional Control Scale

The Poor Attentional Control (PAC) scale serves as a trait measure of attentional function in everyday life. It was administered before the Sternberg working memory task to avoid the possibility that participants' perceptions of their performance might influence responses. The PAC consists of 15 items identified by factor analysis (Huba et al., 1982) from the larger 36-item Imaginal Processes Inventory (Singer & Antrobus, 1970). As in previous studies (Berry, Demeter, et al., 2014; Berry, Li, et al., 2014; Jang et al., 2020; Kim et al., 2017), participants completed all 36 items but analyses focused on the PAC scale. For each item, the participant indicated how true the statement was for them (1 = *not all true of me*; 5 = *very true of me*).

Modified NASA Task Load Index

The NASA Task Load Index (NASA-TLX) measures subjective workload experienced during the task (Hart & Staveland, 1988). It was administered after each Sternberg run. The original NASA-TLX has six subscales that ask the following: (1) How mentally demanding was the task? (Mental Demand); (2) how physically demanding was the task? (Physical Demand); (3) how hurried or rushed was the pace of the task? (Temporal Demand); (4) How successful were you in accomplishing what you were asked to do? (Performance); (5) How hard did you have to work to accomplish your level of performance? (Effort); (6) How insecure, discouraged, irritated, stressed, and annoyed were you? (Frustration). We added two relevant to our specific hypotheses: (7) How distracted were you during the task? (Distraction) and (8) How motivated were you during the task? (Motivation). Participants respond using a 0 (very low) to 100 (very high) point scale, except for the Performance scale, which uses a "reversed" scale, 0 (perfect) to 100 (failure).

Other questionnaires

We included other questionnaires for exploratory analyses and to maintain consistency with our previous report (Jang et al., 2020). These included the Motivation and Thinking Content scales from the Dundee Stress State Questionnaire (DSSQ; Matthews et al., 2002, 2013) and the Intrinsic Motivation Inventory (IMI; Ryan, 1982). Because of their exploratory nature, we do not discuss these at length in the Results, but provide the summary data in the Supplemental Material S16-S21 for completeness.

Procedure

Participants first completed informed consent procedures, followed by the health and demographic questionnaire and the PAC questionnaire. Participants then received instructions for the Sternberg task and completed a practice run consisting of 10 trials of set sizes 3, 5, or 7. Participants had to get more than 80% correct on the practice trials to proceed to the main task. If not, they repeated the practice. Failure to reach criterion within three practice runs terminated the session.

After the practice run, participants in the loss incentive condition were endowed with $15. This money was put on the table in front of them. They were told that it was theirs to keep for good performance (in addition to the hourly compensation for study participation), with 30 cents deducted for every incorrect trial. Performance feedback (trial-level accuracy and run-level percent incorrect) and incentive feedback (the amount of money lost in the current run) were given after each trial. At the end of each run, the experimenter removed the amount lost and placed the new amount on the table. Participants in the control condition received identical performance feedback but without incentive. Participants then completed the modified NASA-TLX questionnaire with reference to the run they had just completed. After the final run of the Sternberg task and the corresponding NASA-TLX questionnaire, they completed the remaining questionnaires. They next completed the MMSE (older adults only) and ERVT. Lastly, they were thanked, debriefed, and given the hourly compensation for their participation.

Analyses

Our central question was whether the incentive manipulation would have opposite effects (increases for young adults, decreases for older adults) on overall performance, diffusion model parameters (especially drift rate), and motivation in young vs older adults. Secondary analyses of within-subjects factors (different trial types) and subjective measures guided interpretation of the main analyses. We used Bayesian multilevel models (Kruschke, 2014; Lee & Wagenmakers, 2014). Unless otherwise noted, all analyses used the analysis package default non- or weakly-informative priors. Orthonormal contrasts ensured that the intercept corresponded to the unweighted grand mean and that the marginal prior was same for all factor levels (Rouder et al., 2012; Singmann, 2020). A random intercept for each participant controlled for individual variability (Field et al., 2012).

Our description of the results in the main text focuses on those analyses relevant to testing our conceptual hypotheses. The full modeling results, marginal means, power analyses, and other details can be found in the Supplemental Material.

Analyses were conducted in the probabilistic programming language Stan (Carpenter et al., 2017; Stan Development Team, 2018) using the wrapper package brms (Bürkner, 2017) in R version 4.0.2 (R Core Team, 2017). The brms package uses a Markov chain Monte Carlo (MCMC) sampling procedure to compute posterior samples. We fit the models with three chains and 6,000 iterations, 2,000 of which were the warm-up phase. To assess convergence, we made sure that the R-hat convergence diagnostic was close to 1 and less than 1.1, visually inspected the chains, and verified that the bulk effective sample size was greater than 100 times the number of chains (Bürkner, 2016; Kruschke, 2014). To validate the models, we performed posterior predictive checks to inspect whether the data generated from draws from the posterior show patterns consistent with those observed in the actual data. These convergence checks and posterior predictive checks were adequate for the reported models. However, the reaction time model had relatively low bulk effective sample size; to address this, we increased the number of iterations by 2,000 for this model. For the fixed effects, we report the point estimate and 95% credible interval of the posterior samples of the regression coefficients. Effects were considered significant if this 95% credible interval did not include zero. For the set size analyses, the regression coefficient β_{SS1} describes the difference between set size 6 vs. set size 8 and β_{SS2} the difference between set size 4 vs. set sizes 6 and 8. We set the contrast this way because set size 4 is likely sub-span for both groups, so the contrast between set size 4 vs. set sizes 6 and 8 represents the transition from sub-span to or above span, whereas the contrast between set size 6 vs. set size 8 represents changes in difficulty at or above span. All other factors have two levels and were treated as categorical variables.

Accuracy and response time analyses

Age group (younger, older adults), incentive condition (control, incentive condition), set size (4, 6, 8 letters), retention interval (4, 16 seconds), and all interaction terms were included as predictors. For accuracy, a logistic regression model was fitted since outcomes are binary (0 = incorrect, 1 = correct). For reaction time, linear regression was fitted on raw reaction time data for correct trials[3].

Diffusion model analysis

We conducted diffusion model analyses to examine the effects of loss incentive on different processing components. Diffusion models integrate accuracy and response time data to understand decisions in two-choice tasks (Ratcliff, 1978; Ratcliff et al., 2004; Ratcliff & Smith, 2004; Wagenmakers, 2009). Diffusion models assume that evidence available to the decision maker is represented in a one-dimensional quantity. This evidence accumulates over time and the decision is made when accumulated evidence reaches a threshold of either option. Among various extensions of the diffusion models (see Ratcliff & Smith, 2004, for review), we used the Wiener diffusion model since it has the simplest complete form (Wabersich & Vandekerckhove, 2014) and includes the four parameters of primary interest.

[3] In addition to raw reaction time data, log transformed reaction time data were fit to the models to adjust for general slowing in older adults' responses. We report the raw reaction time results in the main text since the results were mostly consistent with log transformed reaction time results. Results for log transformed data are reported in the Supplemental Material.

The four parameters of the Weiner diffusion model are *drift rate, boundary separation, initial bias*, and *non-decision time*. Drift rate represents the quality of the stimulus representation. This corresponds to how fast evidence is accumulating. In our model, the upper boundary was set as making the “old item” response and the lower boundary was set as making the “new item” response. Therefore, drift rates for old item trials have positive values (evidence accumulating towards the upper boundary), whereas drift rates for new item trials have negative values (evidence accumulating towards the lower boundary). For ease of comparison, we report absolute values of drift rates in this paper. Boundary separation represents how much evidence needs to be accumulated before making a response. Boundary separation is related to speed-accuracy trade-offs: higher values indicate an emphasis on accuracy (requiring more evidence despite longer time for accumulation); lower values indicate emphasis on speed (faster responses despite less accumulated evidence). Initial bias (bias, hereafter) represents the bias towards the “old” or “new” response before evidence accumulation begins. The product of the bias and the boundary separation decides the starting point in evidence accumulation. A bias equal to 0.5 indicates an unbiased starting point, halfway between the lower and upper boundaries. A bias greater than 0.5 indicates bias towards the upper boundary (making an “old item” response), and a bias less than 0.5 indicates bias towards the lower boundary (making a “new item” response). Since our task had equal numbers of new and old item trials, the optimal value of the bias parameter was 0.5. Lastly, the non-decision time parameter represents the time spent on processes not related to evidence accumulation, such as motor response time and encoding time.

We used a hierarchical Bayesian approach to fit the data to the Wiener diffusion model, using the RWiener (Wabersich & Vandekerckhove, 2014) package. We generally followed the estimation procedures introduced in Singmann (2017). Drift rate was predicted by the probe type (new, old item trial), age group, incentive condition, set size, retention interval, and all interaction terms. Boundary separation and bias were predicted by age group, incentive condition, set size, retention interval, and all interaction terms. Non-decision time was predicted by age group, incentive condition, and their interaction.

For bias, rather than the default non- or weakly-informative priors, we used a normal distribution with mean of 0.5 and standard deviation of 0.2 as a prior, based on the estimates from a prior study (Spaniol et al., 2011). Non-responses due to exceeding response time limit in the task were excluded from the analysis (0.5% of the total data).

Modified NASA-TLX analysis

Age group, incentive condition, and their interaction were included as predictors.

Results

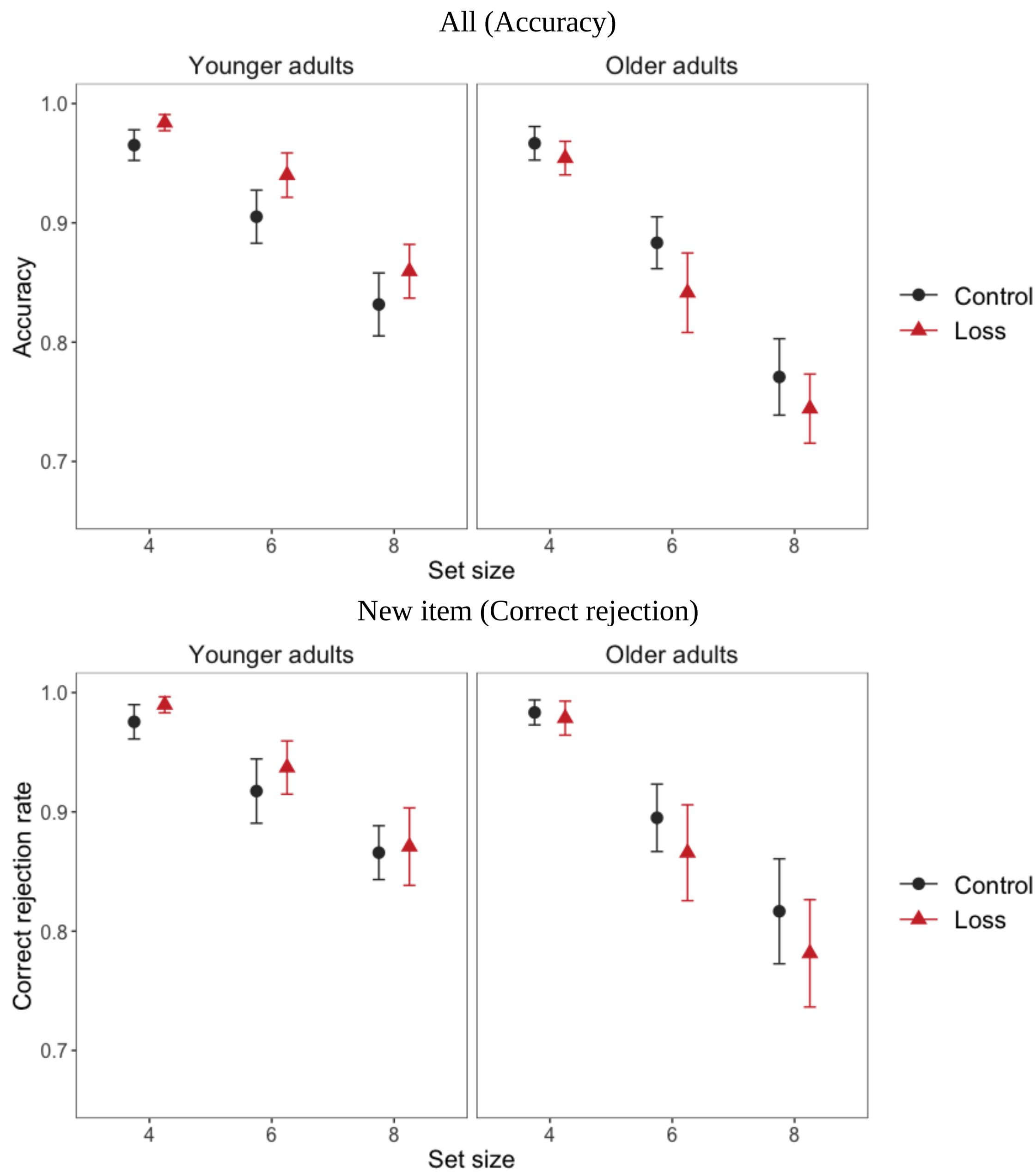
Table 3-1. Demographics and self-reported Poor Attentional Control

		Young Control (n = 31, 24 f)	Young Loss (n = 35, 26 f)	Old Control (n = 24, 17 f)	Old Loss (n = 28, 15 f)
Age					
	Mean	19.26	19.51	68.83	68.04
	SD	1.71	2.12	4.86	5.75
Years of Education					
	Mean	13.27	13.59	17.71	17.07
	SD	1.43	1.90	1.76	1.94
ERVT					
	Mean	17.63	20.04	31.15	29.82
	SD	5.83	4.67	6.92	7.29
PAC Mind-Wandering					
	Mean	14.97	14.31	13.50	11.43
	SD	3.45	3.31	3.01	2.38
PAC Boredom					
	Mean	13.97	13.57	10.62	11.25
	SD	3.20	2.90	2.87	3.69
PAC Distractibility					
	Mean	15.74	16.31	13.08	12.79
	SD	3.79	3.40	3.41	3.42
MMSE					
	Mean	n/a	n/a	28.79	28.68
	SD	n/a	n/a	0.98	1.22

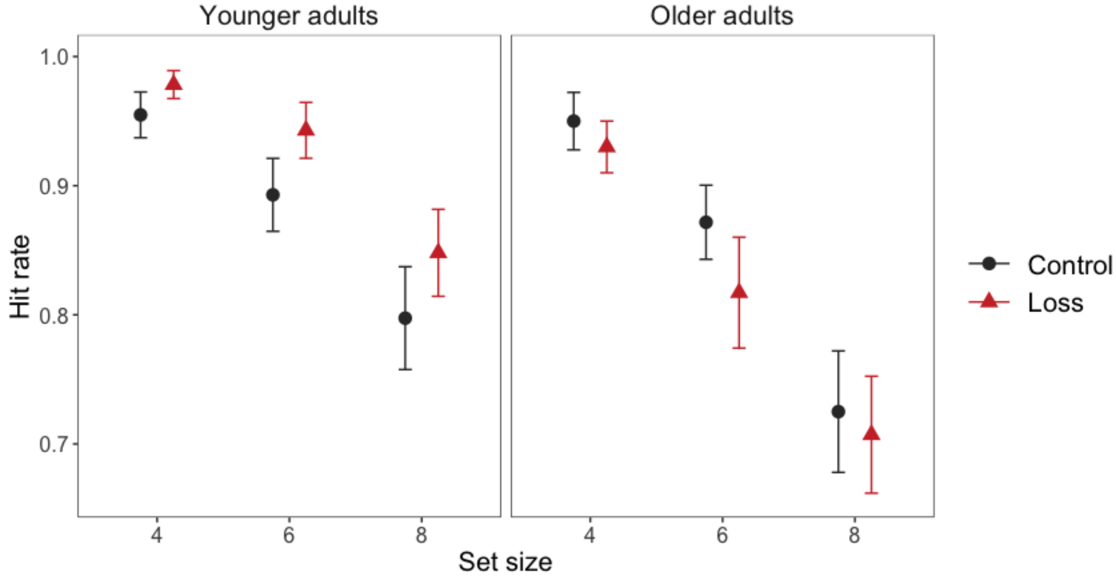
f, female; ERVT, The Extended Range Vocabulary Test; PAC, the Poor Attentional Control scale; MMSE, Mini-Mental State Examination

Behavioral results

Figure 3-2. Accuracy data



Old item (Hit)



Top panels show accuracy for all trials. Middle and bottom panels show accuracy for new and old item trials, respectively. Control condition: black circle, Loss condition: red triangle. Error bars show 95% confidence interval of the data.

Table 3-2. Reaction time data

Age	Condition	Set size	All items	New items	Old items
YA	Control	4	1.027 [0.957 1.096]	1.028 [0.949 1.107]	1.025 [0.961 1.089]
		6	1.119 [1.037 1.201]	1.140 [1.051 1.229]	1.097 [1.011 1.183]
		8	1.153 [1.066 1.239]	1.180 [1.085 1.275]	1.126 [1.040 1.212]
YA	Loss	4	0.987 [0.925 1.048]	0.984 [0.921 1.048]	0.990 [0.926 1.053]
		6	1.090 [1.019 1.160]	1.135 [1.053 1.218]	1.044 [0.979 1.109]
		8	1.117 [1.046 1.188]	1.149 [1.074 1.224]	1.086 [1.011 1.161]
OA	Control	4	1.265 [1.166 1.363]	1.293 [1.192 1.393]	1.236 [1.136 1.335]
		6	1.413 [1.321 1.506]	1.456 [1.355 1.556]	1.372 [1.276 1.467]
		8	1.464 [1.363 1.566]	1.494 [1.382 1.606]	1.437 [1.335 1.538]
OA	Loss	4	1.243 [1.171 1.315]	1.243 [1.157 1.329]	1.245 [1.175 1.315]
		6	1.349 [1.263 1.434]	1.373 [1.266 1.480]	1.330 [1.258 1.401]
		8	1.396 [1.311 1.481]	1.402 [1.302 1.502]	1.396 [1.316 1.475]

Mean and 95% confidence interval for reaction time data are shown. Only correct trials were used to compute these summaries. All items: both new and old item trials.

Our primary question concerned the effect of the loss incentive on performance and motivation in young and older adults. Secondarily, we hypothesized that the effects of the incentive, and age differences therein, might be larger for the longer retention interval. The latter hypothesis was not supported: The retention interval factor did not interact with the effects of incentive (Accuracy: $\beta_{RI1 \times Incentive1}$ = 0.042 [-0.086 0.171], $\beta_{RI1 \times Age \times Incentive1}$ = -0.067 [-0.249 0.114]; Reaction time: $\beta_{RI1 \times Incentive1}$ = 0.011 [-0.001 0.023], $\beta_{RI1 \times Age \times Incentive1}$ = 0.001 [-0.016 0.017]). Instead, the retention interval had surprising effects that were independent of the incentive manipulation. We report those findings in a separate section. The analyses reported below focus on our primary predictions for the age × incentive interaction, with the secondary question of whether those effects may be greater at larger set sizes.

Overall accuracy data (Figure 3-2) replicated typical effects of age and set size: Young adults outperformed older adults (β_{Age1} = -0.426 [-0.579 -0.275]; marginal model estimate[4] of young adults = 0.939 [0.932 0.946], older adults = 0.894 [0.882 0.906]), and there was a decline in performance with increasing set size ($\beta_{Setsize1}$ = -0.548 [-0.625 -0.473], $\beta_{Setsize2}$ = 1.391 [1.256 1.533])[5]. See S1 for full model results.

As predicted, the incentive manipulation had opposite effects on the performance of young and older adults, ($\beta_{Age1 \times Incentive1}$ = -0.402 [-0.617 -0.195]). Young adults in the loss condition had higher accuracy (marginal model estimate = 0.953 [0.944 0.960]) compared to those in the control condition (0.923 [0.910 0.934]). Older adults in the loss incentive condition (0.880 [0.862 0.897]) tended to show decreased accuracy compared to those in the control condition (0.907 [0.890 0.922]), with a small overlap.

For the reaction time data (Table 3-2) there was no incentive effect ($\beta_{Incentive1}$ = -0.031 [-0.086 0.023], nor was there an age × incentive interaction on reaction time ($\beta_{Age1 \times Incentive1}$ = -0.008 [-0.086 0.071]). We replicated typical effects of slower responses for older adults, and at larger set sizes (see S2 for full model results).

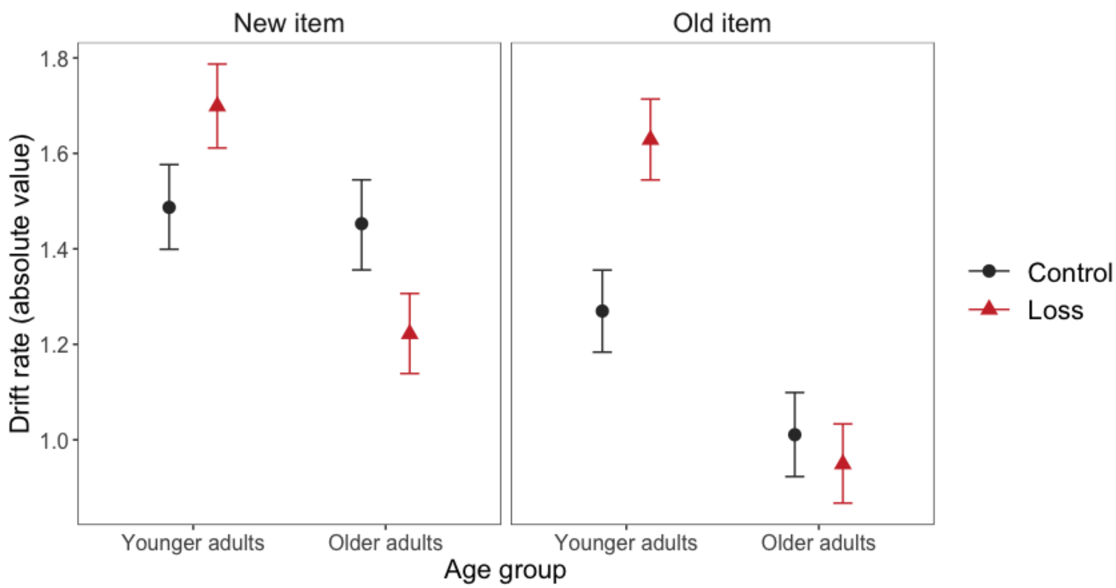
In short, the basic behavioral data suggest that incentive had opposite effects on accuracy for younger and older adults, and no significant effects on response time. The patterns were consistent when we analyzed the effects separately for new and old item trials (middle and bottom panels in Figure 3-2; full model results and marginal means in S1-S2 and S6-S7). Across analyses there were a few interactions involving set size, but no systematic pattern suggesting an increase or decrease in incentive effects as a function of cognitive load.

[4] The marginal model estimates are the mean and 95% credible interval of the posterior predictive values (model predictions) of the outcome variable based on posterior samples of the parameters in the model.
[5] As described in the Methods, β_{SS1} tests the difference between set size 6 vs. set size 8 and β_{SS2} tests the difference between set size 4 vs. set sizes 6 and 8.

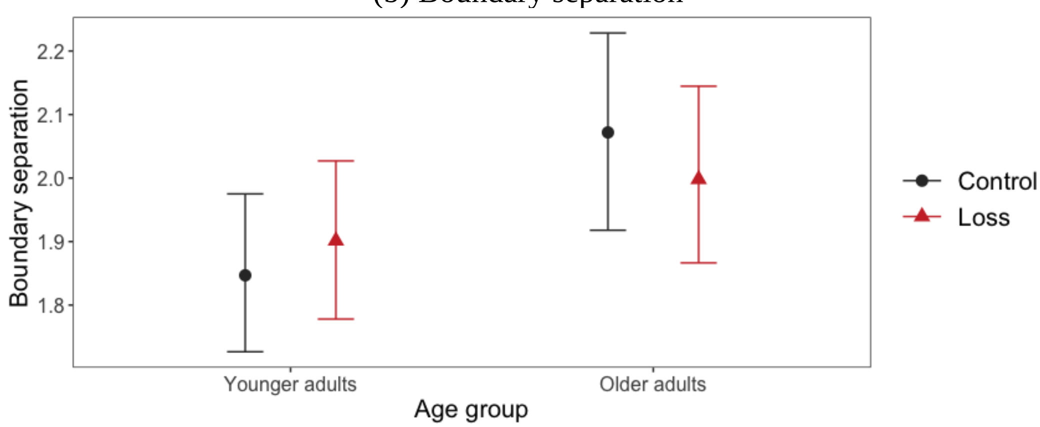
Diffusion model results

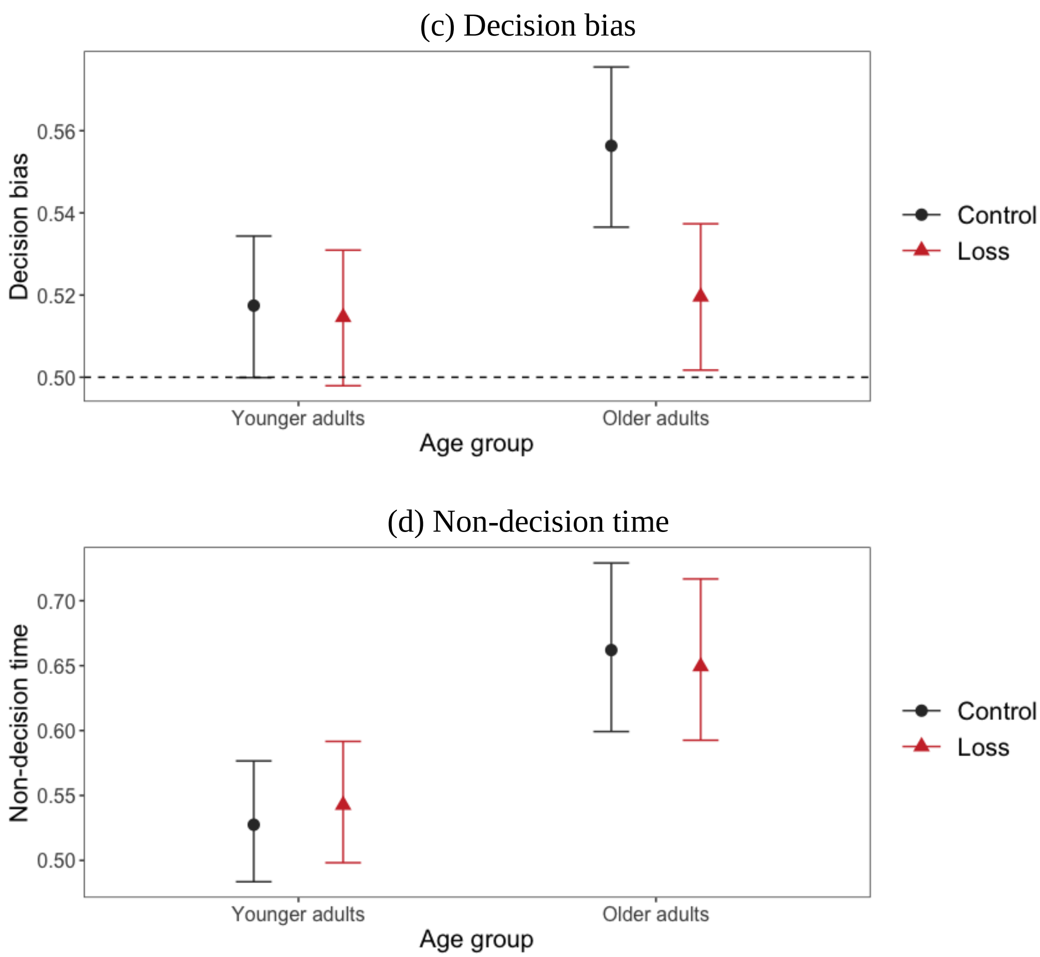
Figure 3-3. Diffusion model parameters

(a) Drift rate



(b) Boundary separation





(a) Drift rate. Absolute values are shown for the ease of comparison. (b) Boundary separation. (c) Decision bias. Dashed line (0.5) means no bias. (d) Non-decision time. Control condition: black circle, Loss condition: red triangle. Error bars show 95% credible interval of marginal model estimates.

Drift rates

The drift rate parameter was used to examine the effects of loss incentive and other experimental factors on the quality of memory representation (Figure 3-3a). Making a "new item" response corresponded to hitting the lower boundary. Making an "old item" response corresponded to hitting the upper boundary. Thus, successful performance requires a negative drift rate for new item trials and a positive drift rate for old item trials. For ease of comparison, we report absolute value of the drift rate estimates for all probe types.

Our main question was whether the loss incentive would have differential effects on the quality of the memory representation (drift rate) for younger vs. older adults. This was indeed the case (Figure 3-3a). The size of the incentive effect for each age group varied by probe type (old, new item), ($\beta_{\text{ProbeType1} \times \text{Age1} \times \text{Incentive1}}$ = -0.305 [-0.370 -0.242]). Young adults showed a larger beneficial effect of the incentive for old item trials than for new item trials (old: control = 1.270 [1.184 1.356], loss = 1.629 [1.544 1.714]; new: control = 1.487 [1.399 1.577], incentive = 1.699 [1.611 1.787]); whereas for older adults loss-induced impairments were larger for new item trials than for old item trials (old: control = 1.011 [0.923 1.099], loss = 0.949 [0.867 1.033]; new: control = 1.453 [1.356 1.545], incentive = 1.222 [1.139 1.306]). See S4 for full model results.

We did not find strong evidence for the alternative hypothesis that loss incentive might increase cognitive load for older adults, and thus show its most detrimental effects at the highest set sizes. Instead, although the results were complex, they tended in the opposite direction, especially for young adults' response to new items. Given the complex patterns of incentive × set size interaction seen here and in other studies (e.g., Manga et al., 2020; Thurm et al., 2018), we do not discuss them further. Full model results are presented in Supplemental Material (S4 for the contrasts for this and other diffusion model parameters; S8 and S14 for the marginal means).

Boundary separation

The boundary separation parameter was used to examine whether loss incentive affected speed-accuracy tradeoffs (Figure 3-3b). We replicated standard age effects (e.g., Starns & Ratcliff, 2010, 2012): older adults set higher decision boundaries (greater emphasis on accuracy vs speed) than did younger adults (β_{Age1}= 0.058 [0.009 0.107]) with a slight overlap in the marginal model estimates (young adults = 1.873 [1.787 1.961], older adults = 2.034 [1.936 2.141]). We did not find evidence that the incentive affected the speed-accuracy tradeoff for either group ($\beta_{Incentive1}$ = -0.003 [-0.050 0.046]; $\beta_{Age1 \times Incentive1}$ = -0.033 [-0.103 0.039, c.f. Chiew & Braver, 2011; Thurm et al., 2018).

Response bias

We next examined whether loss incentive introduced a bias toward old or new responses (Figure 3-3c). There was a trend towards an age × incentive interaction, though it did not reach traditional significance levels ($\beta_{Age1 \times Incentive1}$ = -0.068 [-0.139 0.004]). Specifically, as shown in Figure 3-3c, older adults in the loss incentive condition showed less bias towards “old item” responses (0.520 [0.502 0.537]) compared to those in the control condition (0.556 [0.537 0.576]), with minimal overlap. There was no incentive effect in younger adults (control = 0.517 [0.500 0.534], loss = 0.515 [0.498 0.531]). This suggests the loss incentive may have reduced the typical liberal bias seen in older adults, but should be interpretatively cautiously given the marginal results and that this was not one of our original predictions.

Non-decision time

We examined the non-decision parameter to ask whether loss incentive affected processes (e.g., motor speed) not related to the decision-making (Figure 3-3d). We replicated standard effects of longer non-decision times for older adults (Ratcliff et al., 2001; Theisen et al., 2021; β_{Age1} = 0.144 [0.078 0.207]; young adults = 0.535 [0.503 0.569], older adults = 0.655 [0.611 0.702]). There was no incentive effect ($\beta_{Incentive1}$ = 0.003 [-0.064 0.075]) nor age × incentive interaction ($\beta_{Age1 \times Incentive1}$ = -0.024 [-0.109 0.064]).

Modified NASA-TLX results

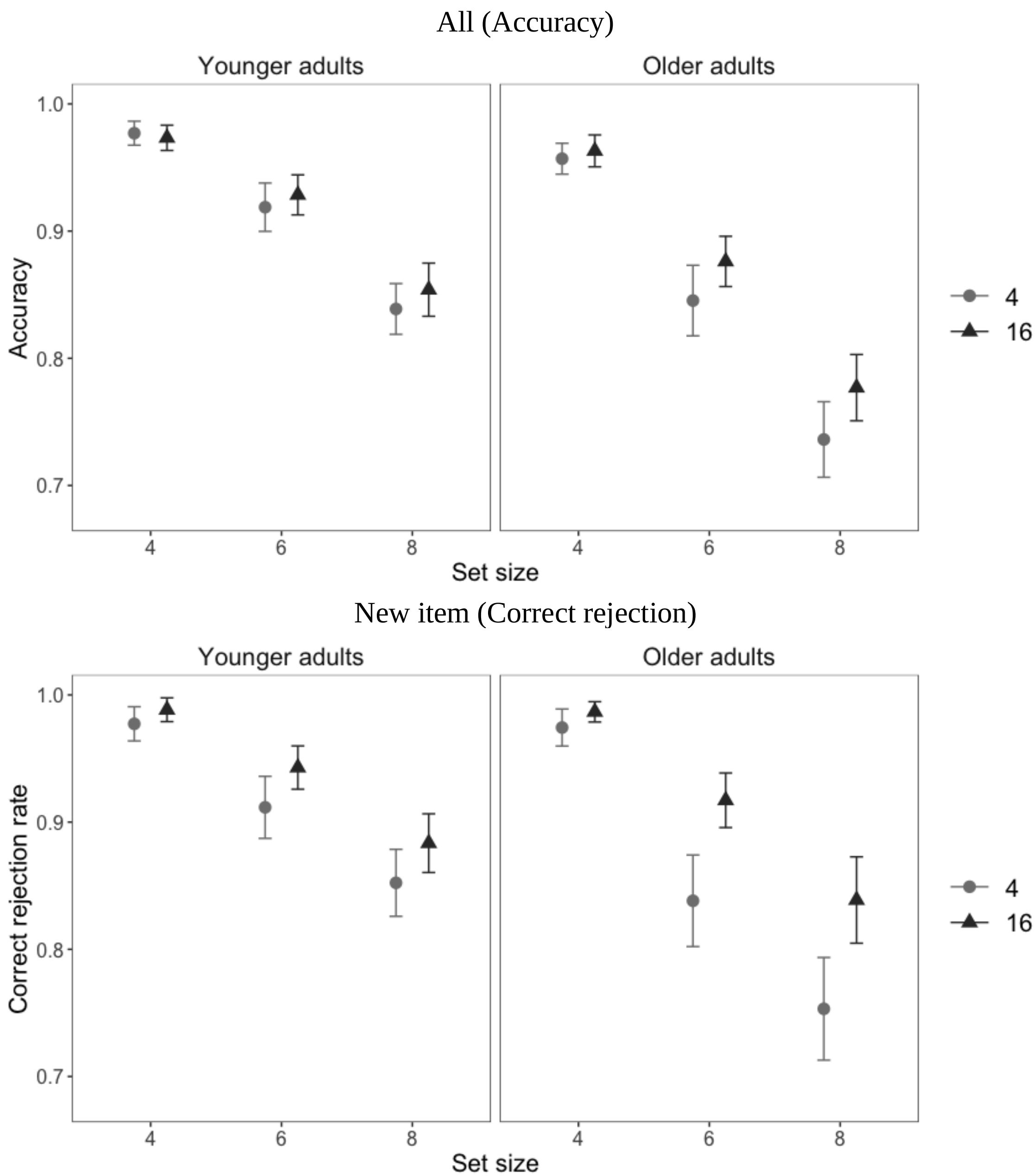
Our primary interest in examining the NASA-TLX data was to see if subjective experience differed by incentive condition and if those effects interacted with age group. In a previous study with a high-constraint task and little opportunity for disengagement (the experimenter spoke letters and numbers to the participant, who had to immediately recite them back in alphanumeric order), we found that loss incentive increased frustration and level of perceived demand, but not the effort to meet that demand (Jang et al., 2020). In discussing those results, we proposed that task constraints may mediate whether motivation effects are more evident in performance or perceived demand: In highly constrained tasks, performance is less reliant on self-initiated engagement, and thus loss-incentive effects may be more evident in subjective measure such as perceived demand. The opposite might be true in less-constrained tasks, such as that used here, where participants can escape increased perceived demand by reducing their performance. With the caveat that the tasks differ in several ways, the results were consistent with those predictions: The incentive had performance effects, but no effect on the mental demand and frustration subscales that had shown effects in Jang et al. (Full model results and marginal means for all subscales in Supplemental Material S5 and S12).

There was an age × incentive interaction on two subscales less related to perceived demand, the self-reported performance subscale ($\beta_{Age1 \times Incentive1}$ = -5.892 [-11.589 -0.188]) and the newly-added motivation subscale ($\beta_{Age1 \times Incentive1}$ = -9.419 [-16.035 -2.779]). The patterns for the self-report, perceived performance subscale paralleled the working memory accuracy data: Younger adults in the loss condition reported numerically higher success in the task compared to those in the control condition (control = 76.164 [71.574 80.739], loss = 79.832 [75.558 84.031]), whereas older adults showed the opposite pattern (control = 72.688 [67.645 77.984], loss = 64.574 [59.863 69.300]). There was also a significant age effect on self-reported performance (β_{Age1} = -6.667 [-10.819 -2.608]): Younger adults reported higher success in the task compared to older adults (young adults = 77.998 [74.872 81.088], older adults = 68.631 [65.162 72.065]). In short, incentive and age had similar effects on actual and self-perceived performance.

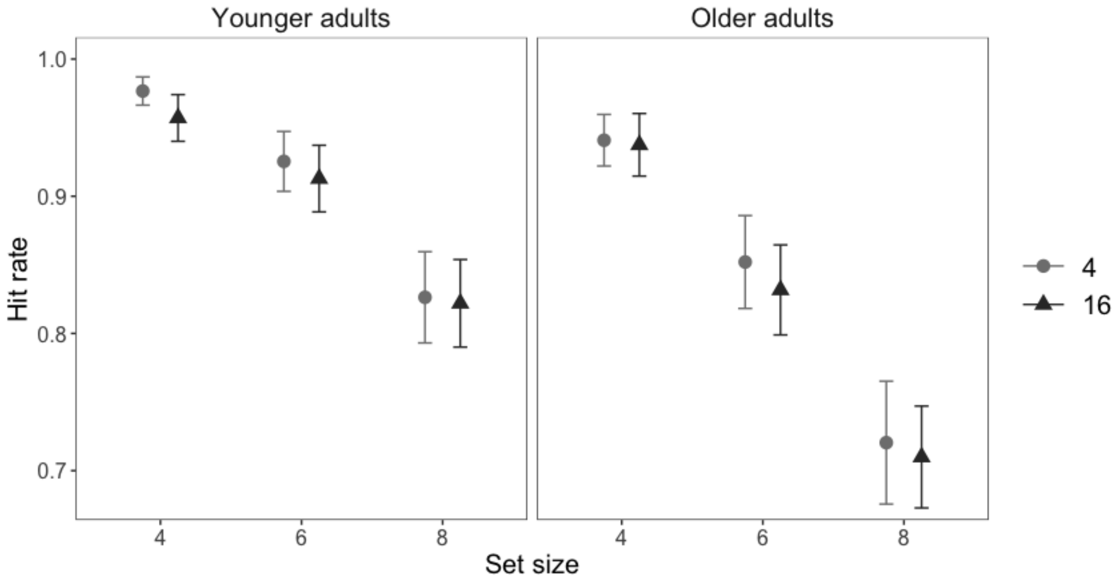
The age × incentive interaction on the motivation subscale suggested that loss incentive increased motivation for younger adults (control = 65.487 [60.326 70.553], loss = 76.694 [71.814 81.634]), but decreased motivation for older adults (control = 84.049 [78.016 89.984], loss = 76.026 [70.166 81.889]). There was also a significant main effect of age (β_{Age1} = 6.098 [1.615 10.773]), in the opposite direction as that seen for the self-reported performance subscale: Younger adults reported lower motivation in the task compared to older adults (young adults = 71.091 [67.624 74.691], older adults = 80.038 [76.012 84.111]).

Retention interval effect

Figure 3-4. Accuracy data (Retention interval)



Old item (Hit)



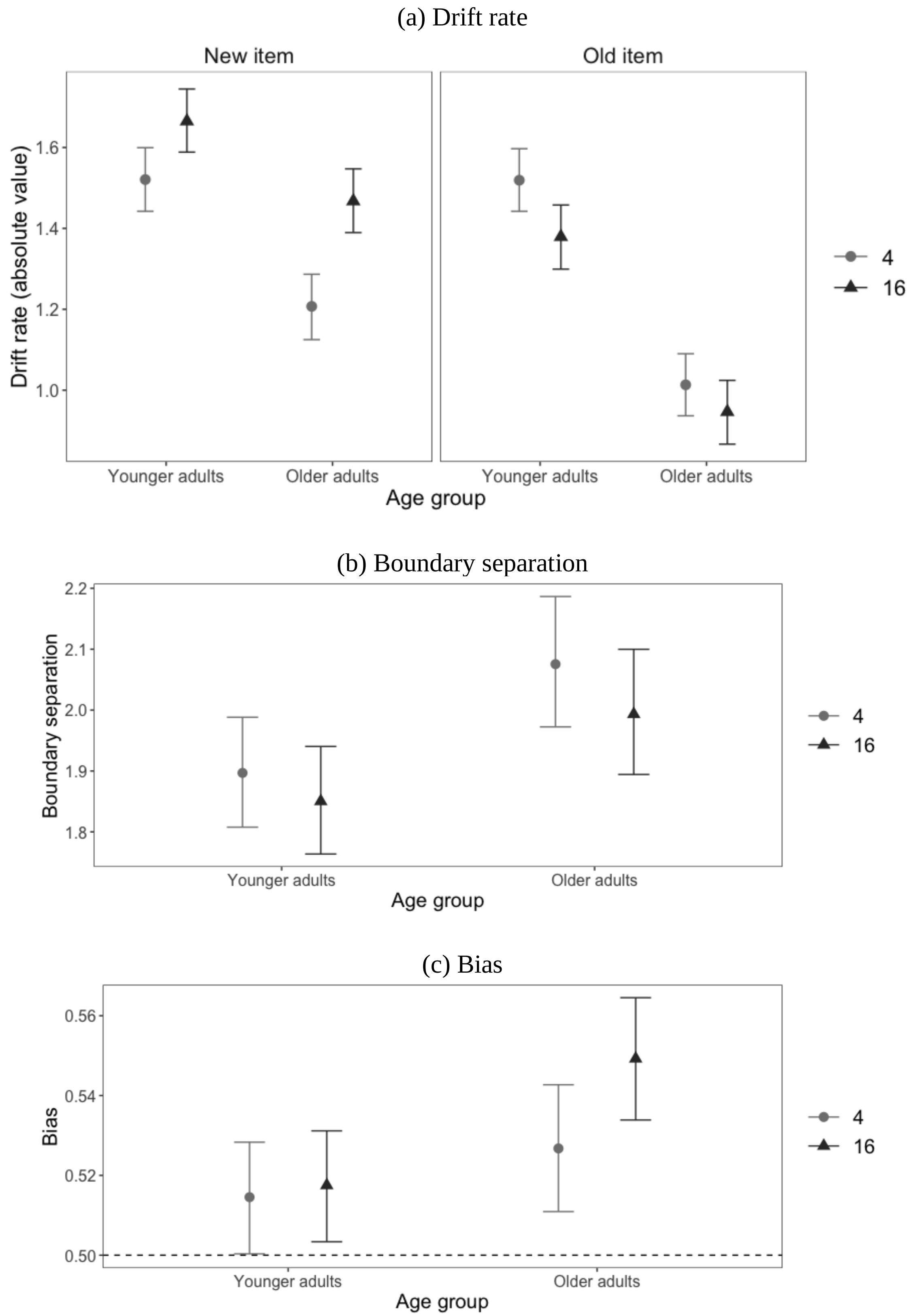
Top panels show accuracy for all trials. Middle and bottom panels show accuracy for new and old item trials, respectively (collapsed across control and loss incentive conditions). Shorter retention interval (4 s): gray circle, Longer retention interval (16 s): black triangle. Error bars show 95% confidence interval of the data.

Table 3-3. Reaction time data (Retention interval)

Age	RI	Set size	All items	New items	Old items
YA	Short (4 s)	4	0.994 [0.950 1.038]	0.988 [0.939 1.037]	0.999 [0.954 1.043]
		6	1.121 [1.068 1.174]	1.187 [1.122 1.252]	1.061 [1.010 1.113]
		8	1.167 [1.109 1.225]	1.219 [1.158 1.279]	1.118 [1.055 1.182]
YA	Long (16 s)	4	1.017 [0.966 1.068]	1.020 [0.963 1.077]	1.015 [0.965 1.065]
		6	1.086 [1.028 1.143]	1.094 [1.031 1.156]	1.077 [1.016 1.137]
		8	1.101 [1.044 1.157]	1.113 [1.049 1.177]	1.088 [1.031 1.146]
OA	Short (4 s)	4	1.247 [1.189 1.305]	1.251 [1.189 1.314]	1.244 [1.183 1.305]
		6	1.424 [1.361 1.488]	1.480 [1.399 1.561]	1.377 [1.316 1.438]
		8	1.491 [1.425 1.556]	1.530 [1.449 1.611]	1.458 [1.395 1.522]
OA	Long (16 s)	4	1.260 [1.197 1.323]	1.279 [1.207 1.351]	1.238 [1.176 1.300]
		6	1.334 [1.267 1.402]	1.353 [1.275 1.432]	1.318 [1.253 1.383]
		8	1.368 [1.297 1.440]	1.375 [1.298 1.452]	1.367 [1.292 1.442]

Mean and 95% confidence interval for reaction time data are shown. Only the correct trials were used to compute these summaries. RI: retention interval. All items: both new and old item trials.

Figure 3-5. Diffusion model parameters as a function of retention interval



(a) Drift rate. Absolute values are shown for the ease of comparison. (b) Boundary separation. (c) Decision bias. Dashed line (0.5) means no bias. Shorter retention interval (4 s): gray circle, Longer retention interval (16 s): black triangle. Values are collapsed across control and loss incentive conditions. Error bars show 95% credible interval of marginal model estimates.

As explained in the Introduction, our original motivation for the retention interval manipulation was the hypothesis that a longer retention interval would create greater opportunity for the effects of incentive (whether positive or negative) to manifest. This hypothesis was incorrect. The retention interval factor did not interact with incentive condition.

Instead, the longer retention interval counterintuitively led to higher accuracy (β_{RI1} = 0.099 [0.007 0.188]) and shorter RTs (β_{RI1} = -0.034 [-0.042 -0.025]) (Figure 3-4 and Table 3-3; accuracy: short RI 0.915 [0.906 0.922], long RI 0.925 [0.917 0.932]; RT: short RI 1.243 [1.211 1.275], long RI: 1.195 [1.163 1.227]). The effects appeared somewhat larger for older adults. The interaction with age was not significant for accuracy ($\beta_{Age1 \times RI1}$ = 0.078 [-0.046 0.205]), but the response-time effect was greater for older adults ($\beta_{Age1 \times RI1}$ = -0.021 [-0.033 -0.009]).

A possible explanation of the benefits of longer retention interval is that the longer retention interval might allow greater rehearsal, and thus a stronger memory representation, for old item trials. However, the empirical data do not support this explanation: It was the correct rejection of new items that benefitted from the longer retention interval (accuracy: β_{RI1} = 0.512 [0.323 0.729]; RT: β_{RI1} = -0.052 [-0.064 -0.040]). Old items showed the usual pattern of forgetting over time (accuracy: β_{RI1} = -0.142 [-0.258 -0.025]; RT: β_{RI1} = -0.019 [-0.030 -0.007]) (Figure 3-4 and Table 3-3; Supplemental Material S1, S2, S6, and S7 provide full model results and marginal means).

The diffusion model analyses (Figure 3-5; Supplemental Material S4) indicated a significant retention interval effect on drift rate ($\beta_{ProbeType1 \times RI1}$ = 0.049 [0.004 0.095]). The beneficial retention-interval effects on drift rate were specific to correct rejection of new items (shorter RI = 1.364 [1.307 1.422], longer RI = 1.566 [1.511 1.621]). Drift rate for old items was not significantly different as a function of RI, though effects were in the expected direction (shorter RI = 1.266 [1.212 1.322], longer RI = 1.163 [1.107 1.219]). This retention interval effect on drift rates for the rejection of new items was more prominent for older adults ($\beta_{ProbeType1 \times Age1 \times RI1}$ = 0.067 [0.004 0.131]; Figure 3-5a).

Model estimates of boundary separation suggest that compared to the short RI, the long RI encouraged greater emphasis on speed versus accuracy, with some overlaps (β_{RI1} = -0.023 [-0.035 -0.012], shorter RI = 1.984 [1.914 2.057], longer RI = 1.920 [1.852 1.990]; Figure 3-5b). This does not appear to result from participants strategically favoring a "new item" response after the longer RI. Instead, the results were numerically in the opposite direction, with the bias parameter tending towards more bias toward responding "old" after the longer retention interval than in the shorter retention interval with slight overlaps (β_{RI1} = 0.036 [0.004 0.067], shorter RI = 0.521 [0.510 0.532], longer RI = 0.533 [0.523 0.544]). Though these bias effects visually appeared more prominent in older adults (Figure 3-5c), the age × retention interval interaction did not reach statistical significance ($\beta_{Age1 \times RI1}$ = 0.039 [-0.003 0.083]).

To summarize, the key – though unexpected – finding here was that performance was counterintuitively better after the longer retention interval. This effect was driven by better correct rejection of new items, and the diffusion analyses suggested that the primary mechanism was stronger evidence discriminating the probe from the memory set after the longer retention interval, rather than an increased bias to call the probe "new". As we outline in the Discussion, these results may have implications for current discussions on the role of time in working memory (see below). Given their unexpected and exploratory nature, they should be considered hypothesis-generating, not confirmatory.

Discussion

Working memory demands are part of everyday life. Failure to meet those demands can incur losses, especially for older adults. The present study contributes to our understanding of how loss incentives affect young and older adults' working memory. We found that loss incentive increased young adults' motivation and performance, with opposite effects for older adults. Modeling analyses identified drift rate, a proxy for the quality of the memory representation, as the primary locus of these effects, and self-report measures contextualize and constrain interpretation.

The effects on performance and subjective motivation, rather than mental demand or frustration, were consistent with our hypothesis that the present task would allow participants to modulate performance in accordance with their level of motivation. Likewise, effects were concentrated on drift rate, a measure of the quality of the memory representation, rather than bias, speed-accuracy tradeoffs, or nonspecific factors. These patterns suggest that the loss incentive affected participants' engagement in the task, perhaps in part by affecting how much effort they put into forming the memory representation.

We did not find the predicted amplification of incentive effects at the longer RI. Our original logic was that the longer RI would be a lower-constraint situation allowing greater manifestation of incentive-motivation effects (more rehearsal for motivated subjects, more disengagement and mind-wandering for de-motivated subjects). However, other aspects of the results suggested that such active maintenance processes were not a major factor in this task (see also Souza & Oberauer, 2018, 2020). Instead, the counterintuitive benefits of the longer RI may have more general implications for understanding the effects of time on working memory.

Age differences in the response to loss incentive

As described in the Introduction, different theoretical perspectives suggest competing hypotheses about age differences in the effects of loss incentive. While incentive effects were somewhat smaller for older adults, suggesting reduced responsivity, overall our results aligned with frameworks predicting loss-induced reductions in older adults' motivation and performance. We cannot definitively identify the underlying mechanisms, but the secondary measures and questionnaire data help guide interpretation. Older adults in the loss condition did not give higher frustration ratings, as one might expect if they had greater negative arousal. Nor did we find support for the "cognitive load" idea: Neither incentive effects nor the age × incentive interaction increased with set size, nor did older adults in the loss condition report greater distraction or perceived mental demand. Instead, loss incentive reduced self-rated performance and motivation for older adults. This seems consistent with the possibility that the loss incentive caused older adults to focus on their errors and take a negative view of their performance, de-motivating them and leading them to disengage from the task itself, further worsening their performance.

The highly salient experience of loss in our study may play an important role. That is, the actual *experience* of loss may be important in depressing older adults' motivation and performance, and may have a greater – or even a qualitatively different – effect than the *description* of loss incentive at the start of the task. Some patterns in the data suggest that this may be the case: While for young adults the effects of incentive were evident from the first run, for older adults the two incentive groups had similar results for accuracy, self-rated performance, and motivation on the first run, with the loss-induced drop appearing in the second run and maintained afterwards (Supplemental Material S13).

The age × incentive × run interaction did not reach statistical significance, so the idea that experiencing the loss was a critical factor is a hypothesis for future research, not a strong conclusion. This hypothesis is also suggested by evidence from studies with intermixed, trial-wise incentive structures indicating that losses or gains affect performance and neurophysiological responses on subsequent non-incentivized trials (e.g., Bruening et al., 2018; Chiew & Braver, 2013; Jimura et al., 2010; see Dhingra et al., 2020; Paschke et al., 2015 for evidence that losses may have more generalized effects than gains, especially for older adults). Interestingly, in one of the only studies we are aware of in which older adults performed better under loss- than gain-incentive, the incentive was delivered at the end of the task, not during performance (Horn & Freund, 2020). Moreover, the incentivized task was a prospective memory task performed simultaneously with an ongoing task, consistent with motivation-shift theory's emphasis on how gains and losses interact with age differences in task and goal prioritization.

In the Introduction, we discussed the motivation-shift, positivity effect, and disengagement perspectives as competing views. Given the pattern of results across studies, it may be useful to consider whether they are instead complementary perspectives, explaining different aspects and stages of motivation-cognition interactions. Motivation-shift theory may be especially relevant for how older adults prioritize tasks and goals, especially when there are competing options. The positivity effect, older adults' tendency to direct attention away from negative information, seems to be the most applicable to characterizing older adults' reduced responses to loss-incentive cues in in reinforcement learning and performance studies.

At the cue stage, the negativity associated with losses is still hypothetical and abstract, making it potentially easier for older adults to ignore. When the loss is actually experienced, older adults are just as, or even more, reactive (Bowen et al., 2019; Kircanski et al., 2018;

Samanez-Larkin & Knutson, 2015). This is consistent with an important caveat made about the positivity effect: It is a goal-directed process. Older adults are <u>not</u> expected to direct attention and memory away from highly salient or self-relevant negative information (see reviews by Carstensen & DeLiema, 2018 and Reed & Carstensen, 2012). Reactivity to negative self-relevant information at the outcome stage may disrupt performance and motivation on subsequent trials or lead older adults to disengage to distance themselves from those negative emotions (Barber et al., 2015 for a review of the disruptive effects of age- and self-relevant negative feedback on "real world" measures and career outcomes; Charles, 2010; Hess, 2014).

Although it was not one of the frameworks we originally considered, during the review process it was pointed out that the results might be relevant to regulatory focus theory: the idea that performance is best when incentive structures map onto an individual's sensitivities to the presence or absence of positive outcomes (in which case reward incentives should be more effective) or negative outcomes (in which case loss incentives should be more effective; Shah et al., 1998; see Barber, 2017 for discussion of how in aging it may interact with stereotype threat). On the one hand, young adults' improvement under loss incentive might be interpreted as evidence that they were more prevention-focused than older adults. However, this is difficult to interpret, as our study was not designed to address regulatory-focus theory, and in at least some cases young adults show greater regulatory focus overall than do older adults (Lockwood et al., 2005). Thus, we don't think the present dataset can speak clearly on this question. However, combining the modeling approach and balanced incentives with independent measures and manipulations (e.g., stereotype threat) of regulatory focus could be an interesting direction for future research.

Which processing components are most affected by the loss incentive in young and older adults?

The diffusion modeling results provide insights into how incentives may affect working memory processes in young and older adults. The primary effects were on drift rate, thought to represent the quality of the memory representation and its match with the probe. For young adults, the incentive-related improvement in drift rate was larger for old items than for new items. This suggests that for young adults, incentive enhanced the encoding and/or maintenance of studied items, consistent with the incentive-related increase in motivation on the NASA-TLX.

In contrast, for older adults, the loss-related reduction of drift rate was primarily for new items. Older adults under loss incentive also failed to show the increased liberal response bias (bias towards calling items "old" when uncertain) typically seen on recognition tasks (Huh et al., 2006; Spaniol et al., 2011; Trahan et al., 1986). Older adults' liberal response has been attributed to reductions in controlled processing at both encoding and retrieval, and may also partially reflect a motivation to exhibit "good" memory, colloquially more associated with successful remembering of old items than rejection of new items (see Bowen, Marchesi, et al., 2020 for evidence that motivation influences response bias) When combined with the loss-induced decrease in self-rated performance and motivation for older adults, these results suggest that the loss incentive led older adults to devalue and disengage from the task more generally, perhaps as a way to avoid the negative emotions associated with making errors on a memory task. Studied items may be less sensitive to these effects, as their match to the probe item provides a powerful retrieval cue. Incentive did not affect boundary separation or non-decision time for either age group, suggesting it did not influence speed-accuracy tradeoffs or overall arousal.

Better performance at longer retention intervals: Recognizing the old vs. rejecting the new

The results for the retention interval (RI) manipulation initially seem quite surprising: Better accuracy and faster reaction times at the longer delay. A closer look revealed that this improvement was due to improved correct rejection of new items. For old items, effects were in the expected direction, worse performance at the longer delay. The specific benefit to new items, along with the random, unpredictable intermixing of short and long retention intervals, make it unlikely that the beneficial effects of longer RIs are due to strategic differences in encoding or maintenance (e.g., rehearsal) processes.

Importantly, the diffusion modeling analyses indicated that faster and more accurate rejection of new items at the longer RI was not the result of a greater bias to call items “new”. Instead, the benefits were driven by higher drift rates at the longer delay. For old items drift rate is conceptualized as the quality of the memory representation and its match with the probe (Ratcliff & McKoon, 2008). Thus, for new items, one might think of it as the quality of the non-match - that is, how distinct the probe item is from the memory set.

What constitutes the basis of this distinctiveness? The most obvious answer is time, or the context changes that occur with the passage of time. Most models of working memory focus on the ability to correctly recognize or recall studied items, and whether the forgetting of those items is more likely caused by interference or decay (see reviews by Baddeley, 2012; D’Esposito & Postle, 2015). However, some emphasize the contributions of context to short-term and working memory, with time – or more properly, the internal and external changes that occur over time – being a critical context (see Polyn & Cutler, 2017 for a concise review). Perhaps most relevant is a recent modification of the context retrieval model (Lohnas et al., 2015) to examine age effects, including those in working memory (Healey & Kahana, 2016). According to this conceptualization, context drifts slowly over time, and studied items become associated with the context in place at encoding. If an "old" probe (one matching a studied item) is presented, successful recognition occurs if it reinstates that prior context. "New" probes are correctly rejected as such if their associated context representation is sufficiently different. If context drifts over time, a longer delay between encoding and the probe should result in a more differentiated and distinct context, and thus an easier rejection of the new item – exactly the results obtained here.

These results should be considered with the usual caveats about unexpected findings, but they suggest an interesting testing ground for theories of working memory. It can be difficult to determine whether an old item is forgotten because of decay, interference, or context changes, some of which may interact, and which are likely affected by processes at encoding and during maintenance. New items by definition lack a short-term representation to encode, decay, or maintain, and thus could provide an illuminating alternative perspective.

Limitations and future directions

The failure to find the expected interaction between RI and incentive is one obvious limitation. It may be that the conceptual hypothesis regarding incentive and engagement is incorrect. Alternatively, RI was the wrong manipulation to target engagement, given ongoing debates about the role of rehearsal and other active maintenance processes in working memory (e.g., Hakim et al., 2020; Oberauer, 2019; see Constantinidis et al., 2018 and Lundqvist et al., 2018 for opposing neuroscience perspectives). Well-established manipulations or indices of self-initiated engagement and control on other processing components (e.g., deep vs shallow encoding, familiarity vs recollection at retrieval) should be employed in future studies to provide a more thorough test of engagement and constraint as mediators of incentive effects (see Bowen et al., 2020; Geddes et al., 2018; Spaniol et al., 2014 for related work in long-term memory).

Our central hypothesis – that the loss incentive would improve the motivation and performance of young adults, while decreasing it for older adults – received more support. Some limitations relevant to this hypothesis are prevalent in almost all studies in this domain, such as the cross-sectional age group comparison, and the question of whether monetary incentives have a similar relevance to young and older adults. Likewise, while we have argued that the structure of our task and incentive manipulation may bear closer resemblance to real-world incentivized performance situations than some previous studies, they are all "laboratory tasks" and the generalization to real-world situations remains to be tested. Other limitations and strengths complement the strengths and weaknesses of previous studies. A major difference between our methods and that of many recent studies of incentive effects on cognitive performance is that we used a session-wide, between-subjects manipulation, whereas most recent studies use a trial-wise, within-subjects manipulation. Those within-subjects designs are more efficient, but potentially reduce generalization to real-world performance, and as noted earlier there is increasing evidence for carryover and incentive-context effects that distort estimates of trial-specific effects. Our design makes complementary tradeoffs.

Another major departure from most previous work is the focus on loss, rather than gain. This can be viewed both an innovation and a limitation. Studies focusing on either incentive type are equally subject to the criticism that it is not possible to rule out that "gain" or "loss" effects are more general results of incentive, regardless of valence. Future studies should ideally include both to clarify when gain and loss have congruent events, when they have the opposite effects on the same processes and when they operate via different mechanisms entirely. The present study still makes a unique contribution: Gain incentives typically produce improvement for both young and older adults, occasionally with different magnitudes or on different performance metrics (e.g., speed vs accuracy). Our manipulation of loss incentive produced opposite effects for the two groups. Moreover, losses are theoretically incisive due to competing predictions from different perspectives on age differences on motivation (see Yee et al., 2021 for further discussion of unique insights to be gained from studies using losses and other aversive incentives).

Summary and conclusion

The present work contributes to understanding incentive-cognition interactions and basic processes in working memory. We found that loss incentive was effective in improving motivation, actual performance, and self-perceived performance in young adults, with opposite effects for older adults. Diffusion modeling analyses provided evidence that the primary effects were on the quality of the memory representation (drift rate), rather than strategic bias or speed-accuracy tradeoffs, or nondecision processes (e.g., overall motor speed) that might reflect differences in arousal. With the usual caveats, the subjective measures enriched and constrained interpretation of the performance data, with primary effects on self-rated performance and motivation, rather than frustration, distraction, or mental demand.

Our attempt to test the hypothesis that task constraints influence whether incentive effects manifest more in performance or subjective measures was not successful. Instead, the retention-interval manipulation revealed an intriguing pattern regardless of age or incentive group: Better performance, specifically faster and more accurate correct rejections, at the longer retention interval. The major impact was again on the quality of the memory representation, in this case the efficiency with which a “new” probe could be differentiated from the memory set. This finding is unexpected and should be replicated, but seems consistent with models of working memory that emphasize the role of temporal context. More generally, it suggests that looking at the fate of “new” items may be an under-explored avenue for understanding working memory.

Barrouillet et al. (2018) note that “it is unwise to aim at identifying a unique source to a complex phenomenon like working memory forgetting”. The same likely applies to age differences in the response to incentive. The present results seem consistent with the idea that older adults become de-motivated and disengage when faced with loss incentive, rather than the motivation-shift or positivity effect views. However, as described above, we suspect that these ideas are best viewed as complementary, rather than competing. An important challenge for the field is a more systematic understanding of when each may apply how to translate that understanding to benefit the real-world performance of both young and older adults.

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Supplemental Material

The Supplemental Material for this chapter can be found online at: https://osf.io/9pbkv/

Chapter 4 Computationally Rational Strategies for Integrating Working Memory and Reinforcement Learning: A Bounded Optimality Approach

Introduction

Behavior results from the integration of environmental stimuli and internal processes. Moreover, no task is "process pure" – almost any behavior involves multiple cognitive processes. How those processes are integrated depends on the stable traits of the individual, their current cognitive-emotional state, and the situation. How can we understand these complex and dynamic interactions, especially when they lead to suboptimal results? When we see differences across the lifespan, to what degree do they reflect relatively fixed cognitive limitations vs. potentially more malleable processes such as adaptations to the age-related declines in the cognitive systems?

As we go through life, many situations require us to make choices and learn through trial and error which choices are the most likely to lead to good results. This kind of choice learning is a good example of how our cognition and behavior results from a mix of internal processes as well as environment and task variables. Recent studies have highlighted the joint contribution of working memory (WM) and reinforcement learning (RL) in reward learning (Collins & Frank, 2012, 2018; Rmus et al., 2021; Viejo et al., 2015, 2018; Wimmer & Poldrack, 2022). WM is faster than RL in terms of storing information; however, WM is more capacity-limited and interference-sensitive than RL. Both of these processes play into our learning of different choice options, but how much we rely on each may depend both on our abilities and the situation.

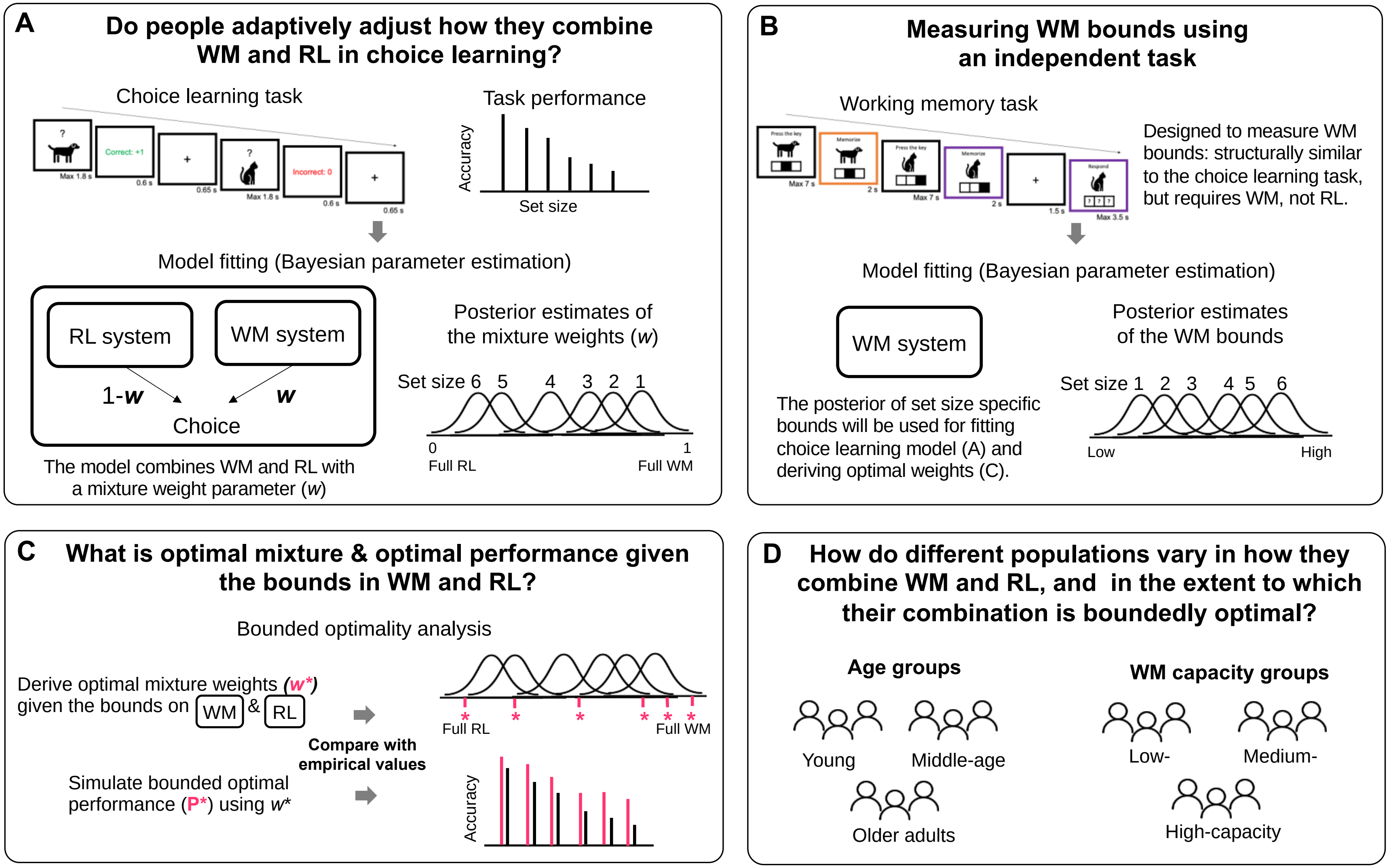
Collins & Frank (2012, 2018) provided a computational framework for estimating the WM/RL tradeoff—i.e., how much an individual relies on working memory (WM) compared to reinforcement learning (RL)—in a choice learning task. In the task, people were asked to learn the rewarding action for the associated stimulus. Importantly, the number of stimulus-action associations (set size 1-6) varied across runs to manipulate the task load. If the amount of information to be learned is within WM capacity and is likely to be used within a few seconds, the adaptive strategy is to rely more on WM than RL. However, if the amount of information to be remembered, or the duration for which it must be remembered, exceeds WM capacity, WM becomes less effective than RL. In such cases, the adaptive strategy is to increase reliance on RL. Collins and Frank modeled this task by including both a WM and RL component, as well as a mixture weight parameter, *w*, that represented the relative contribution of WM as opposed to RL on a trial-level choice.

The current study builds off the Collins & Frank model, but asks in more detail how abilities and demands play into the tradeoffs that people make. Although how to define working memory "capacity" (or if one should even use that term) remains controversial (see discussion by Wilhelm et al., 2013), from a functional and empirical perspective, there are clear limitations on working memory performance that differ across individuals and groups (Jonides et al., 2008; Miller, 1956; Unsworth & Engle, 2007). Knowing the limitations of WM – how much information it can hold – is critical for judging whether WM-RL tradeoffs are 'adaptive' and in accordance with the limitations of that system. Therefore, one important novel feature of the current study is that we measured the set size-specific bounds in WM using an independent WM task and a separate model fitting procedure (Figure 4-1B). This allows us to make more specific predictions for different groups as a function of task load.

First, we can ask whether people adapt to their working memory limitations: Our hypothesis is that as working memory load increases, people will adaptively shift to increased reliance on RL in a way that reflects how well their own WM and RL systems are functioning (Figure 4-1A & Figure 4-1B). In addition to asking whether people are adaptive in shifting from WM to RL, we can also ask the more precise question of whether they make that shift at the optimal point to balance their abilities with the task demands, or do they shift “too early” (at too low a set size) or “too late” (at too high of one)? To ask this more rigorous question, we use a bounded optimality approach (Lewis et al., 2014). Bounded optimality analysis provides a principled way of deriving the computationally rational strategy that leads to maximum utility in a task given the specific level of bounds in the information processing systems. Notably, this analysis reframes individual and group differences research in a way that does not center the behavior of a college-age adult as the normative standard and considers the different strengths and limitations that may be present across different populations (e.g., developmental stages, clinical groups). Further, when behavior is suboptimal, it can shed light on the relative contributions of the individuals’ cognitive limits vs. their strategies or the task. We first conducted this bounded optimality analysis on the whole group to see if the general population is bounded optimal in their strategy and performance (Figure 4-1C).

Finally, we ask how ability and age differences may affect the adaptations to cognitive limitations. On average, older adults have reduced working memory abilities compared to young adults (Borella et al., 2008; Nilsson, 2003; Old & Naveh-Benjamin, 2008; Spencer & Raz, 1995; Verhaeghen et al., 1993; Wingfield et al., 1988), but there are also other important differences between young and older adults such as age differences in dopamine reward systems (Radulescu et al., 2016; Samanez-Larkin et al., 2007), as well as behavioral and neural compensation (Davis et al., 2008; Reuter-Lorenz & Cappell, 2008). Therefore, we further examined whether people adapt to their own bounds, whether we see this adaptation across different age groups, and whether the adaptation is different in different age groups (Figure 4-1D).

Figure 4-1. Overview of the study

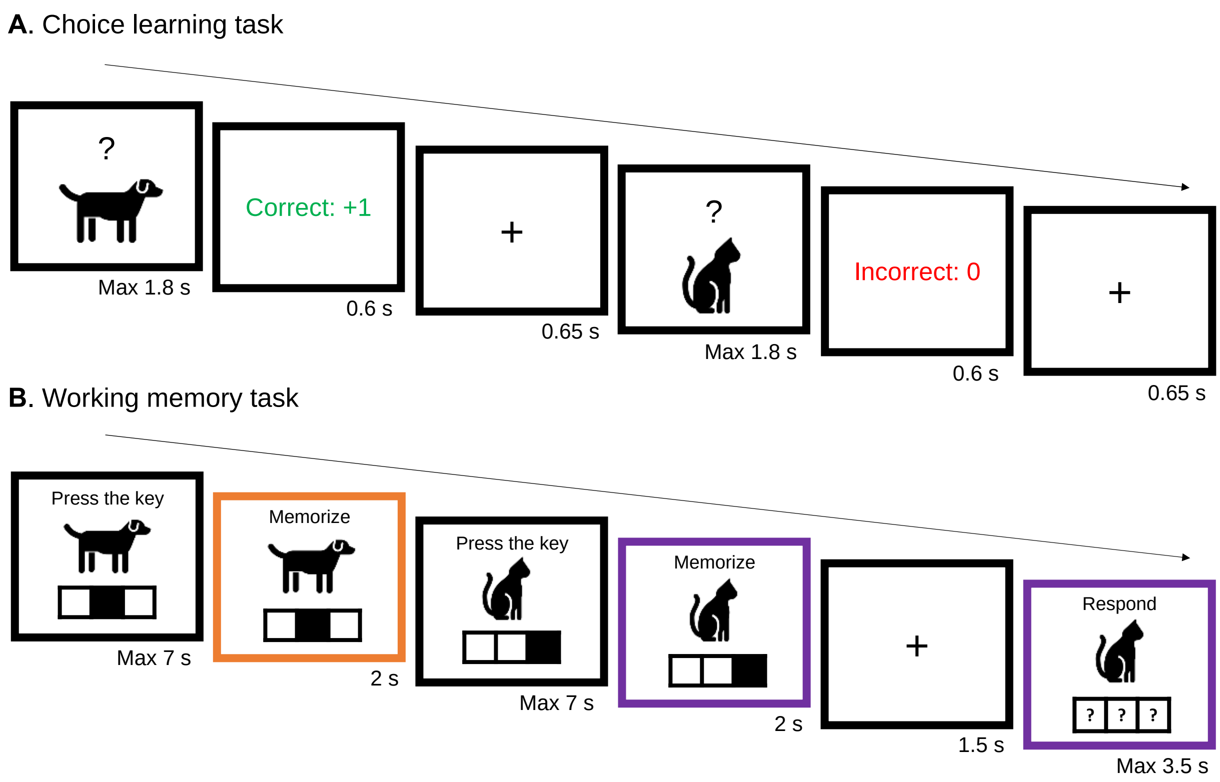


Method

Participants

We recruited 53 young adults (age 20-25), 53 middle-aged adults (age 45-50), and 53 older adults (age 70-75) from an online database Prolific (https://prolific.co/). A total of 159 participants who met the inclusion criteria were included in the analysis. Inclusion rules were age (20-25, 45-50, or 70-75), no ongoing mental health/illness/condition, identification of country of residence as US or UK (for IRB compliance), and passing performance criteria. See Table 4-1 for demographics and Supplemental Material S10 for exclusion data. Participants were compensated at an hourly rate of $9.50/hour. The study was approved by the University of Michigan Institutional Review Board.

Figure 4-2. Experimental tasks



A. An example of two trials in the choice learning task. B. An example of one trial in set size 2 block in the working memory task.

Choice Learning Task

We used a modified version of the choice learning task used in Collins & Frank (2018). As shown in Figure 4-2A, participants were asked to learn the correct action for each stimulus using trial-level feedback. At the start of each trial, a stimulus appeared on the screen with a question mark on the top of the screen. While the stimulus was on the screen, participants were asked to make an action associated with the stimulus. Possible actions were pressing “J”, “K”, or “L” keys using their index, middle, and ring finger, respectively. Then a feedback message (“Correct: +1” if the correct action was made, “Incorrect: 0” if an incorrect action was made, or “Too late” if no response was made within 1.8 seconds) appeared for 0.6 seconds. Feedback was deterministic. The subsequent trial started after a 650-millisecond inter-trial interval. The number of stimulus-action associations (set size) was 1, 2, 3, 4, 5, or 6 and varied randomly across runs. Each stimulus appeared 9 times in a run, and the stimuli appeared in random order. As in Collins and Frank (2018), the number of runs for set sizes 1-6 was in order 3, 6, 4, 3, 3, and 3. The images used in the task were from the Multilingual Picture databank (Duñabeitia et al., 2018). The internal consistency reliability of the choice learning task estimated using the coefficient alpha for the trial data (Cronbach, 1951; Cronbach & Shavelson, 2004) was 0.91 (95% CI: 0.84-0.97).

Working Memory Task

The working memory task was used to measure individual-level and group-level limitations in working memory and make predictions for the choice learning task. Participants completed the working memory task within three days before or after the choice learning task (the order of the tasks was randomized). The stimuli, possible actions, and the set sizes used in the working memory task were the same as the choice learning task. As shown in Figure 4-2B, at the beginning of a trial, an image and a visual cue for a keypress (1x3 cells with one of the cells colored black) appeared in a box with a black outline. Participants were asked to press the key indicated by the visual cue (response limit: 7 seconds). Making the key press response changed the color of the box outline to purple or orange. The combined stimulus (image, key, outline color) remained on the screen for 2 seconds, and participants were instructed to remember the associations. After repeating these steps for all sets (set size 1-6), a probe with the image and the color appeared. The participants' job was to press the correct key associated with the given image and the color in the probe within 3.5 seconds. Set size randomly varied across runs. As in the choice learning task, the number of runs for set sizes 1-6 were in order 3, 6, 4, 3, 3, and 3. The internal consistency reliability of the working memory task estimated using the coefficient alpha for the trial data (Cronbach, 1951; Cronbach & Shavelson, 2004) was 0.89 (95% CI: 0.82-0.95).

Procedure

When participants signed up for the study on Prolific, they first completed an informed consent procedure. They then received instructions for the first task (either choice learning or working memory tasks; task order randomized). After completing the first task, participants were invited back to complete the other task within three days.

We used an individual's performance at the lowest set size (set size 1) as our exclusion criteria to screen out careless participation for both of our tasks. For the working memory task, individuals with average accuracy lower than 90% in set size 1 were excluded from all analyses. For the choice learning task, individuals who did not achieve 90% average accuracy at the 4th iteration or beyond in set size 1 runs were excluded from all analyses. See Supplemental Material S10 for exclusion data.

Computational Models

Choice learning model

A trial-level response in the choice learning task is modeled as a random sample with a probability vector (P_{choice}) for possible actions—i.e., "J", "K", or "L" keypress. The critical assumptions of this model are (1) P_{choice} is the weighted sum of the policy computed from the WM system (P_{WM}) and that of the RL system (P_{RL}), and (2) this mixture weight differs for different set sizes. The weight given to P_{WM} and P_{RL} at each set size is $w_{set\ size}$ and $(1-w_{set\ size})$, respectively (higher values: more reliance on WM).

$$P_{choice} = (w_{set\ size} * P_{WM}) + ((1- w_{set\ size}) * P_{RL})$$

$$Choice_{trial} \sim Categorical(P_{choice})$$

WM system: We assume that (1) the WM system is noisy and (2) the noise level differs for different set sizes. A trial-level WM policy (P_{WM}) is a probabilistic rule of the WM system for choosing an action in response to a stimulus at a given trial. The P_{WM} is a weighted sum of the correct probability vector ($P_{correct}$; see below for details) and the noise vector (P_{noise} = [0.333, 0.333, 0.333]). The weight given to the noise vector at each set size is $\varepsilon_{set\ size}$.

$$P_{WM} = ((1 - \varepsilon_{set\ size}) * P_{correct}) + (\varepsilon_{set\ size} * P_{noise})$$

Notably, a novel component of the current study compared to previous work by Collins et al. (Collins & Frank, 2012, 2018; McDougle & Collins, 2021)was that working memory limitations ($\varepsilon_{set\ size}$ parameters) were not estimated within this model. Instead, they were estimated using a separate fitting procedure using a structurally similar independent working memory task but without the choice-learning component.

$P_{correct}$ is computed as follows: First, for each stimulus *s* and action *a* at trial *t*, the memory value $M_{t+1}(s, a)$ is updated upon encoding the outcome (1 if correct, -1 if incorrect) following this formula:

$$M_{t+1}(s, a) = outcome_t$$

Then, $P_{correct}$ is computed by transforming $M_t(s, a)$ to a probability vector using a softmax function (M(s, a) is multiplied by 50 to model the deterministic nature of working memory):

$$P_{correct} = \exp(50 * M(s, a)) / \Sigma_i(\exp(50 * M(s, a_i))$$

RL system: A trial-level reinforcement learning policy (P_{RL}) is a probabilistic rule of the RL system for choosing an action in response to a stimulus at a given trial. We use a classic RL model to compute P_{RL}. For each stimulus *s* and action *a* at trial *t*, the expected value $Q_{t+1}(s, a)$ is learned upon receiving reward feedback (r_t = 1 for correct, 0 for incorrect) following this formula (Q values are initialized as $1/N_{choice}$, where $N_{choice} = 3$):

$$Q_{t+1}(s, a) = Q_t(s, a) + \alpha * (r_t - Q_t(s, a))$$

Here, the learning rate (α) is a free parameter that decides how fast the RL system will learn from prior experiences. P_{RL} is computed by transforming the expected value $Q_t(s, a)$ to a probability vector using a softmax function:

$$P_{RL} = \exp(\beta * Q(s, a)) / \Sigma_i(\exp(\beta * Q(s, a_i))$$

The exploitation bias (β; inverse temperature, softmax beta) is a free parameter deciding the degree to which differences in expected values are translated into a more deterministic choice.

Working memory model

The goal of the working memory model is to estimate the working memory limitations for each experimental group which will be used to model the WM system in the choice learning model introduced above. The parameters of this model are estimated using the external working memory task data. An identical model is used to model the WM system in the choice learning model.

We used the Bayesian hierarchical modeling approach to estimate the parameters of the models proposed above. In this approach, group-level hyperparameters are added on the individual parameters (Gelman et al., 2013; Kruschke, 2014). This hierarchical structure reduces the effects of sampling variation. The hierarchical parameter settings and their priors were declared as suggested in Ahn et al., (2017). Complete model scripts are available on our OSF page (https://osf.io/2vds9/). For the model fitting procedure, we used the R programming language (version 4.1.0; R Core Team, 2021) and the 'rstan' package (version: 2.21.2; Stan Development Team, 2021). For sampling posteriors, we used the No-U-Turn sampler variant of Hamiltonian Monte Carlo (Hoffman & Gelman, 2011; the default algorithm in rstan) with four chains, drawing 2000 samples from each, and discarding the first 1000 samples. See Supplemental Material S8 and S9 for robustness checks and sensitivity checks (i.e., posterior predictive checks).

Analyses

The analysis plan was pre-registered (https://osf.io/by5hd). To examine the effect of set size on the WM-RL trade-off, we reported the posterior distribution (with the mean and 95% credible interval) of the group-level mixture weight parameter ($w_{\text{set size}}$: the proportion of reliance on WM) for each set size. For statistical inference on when people shift from reliance on WM to reliance on RL, we compared the highest density interval (HDI) of the pairwise difference between the mixture weight at set size 1 ($w_{\text{set size1}}$), which is assumed to represent complete reliance on WM, to that of the other set sizes ($w_{\text{set size = 2, 3, 4, 5, 6}}$). The lowest set size k at which the HDI of the difference score ($w_{\text{set size1}}$ - $w_{\text{set size k}}$) distribution does not contain zero was considered the shifting point.

To examine the effect of WM differences on the WM-RL trade-off, we categorized people into three groups (low, medium, high-performance group, n = 53 per each group because prior work, for example, McDougle & Collins (2021), suggests this number will give reasonable estimates) based on their performance on the working memory task. We fit each group's data separately to our working memory and choice learning models. We report the posterior distributions of the group-level mixture weight parameter ($w_{\text{set size}}$) for each WM performance group. For testing whether a lower performance group will begin to shift from reliance on WM to reliance on RL at lower set sizes than a higher performance group, we estimated the shifting point (see the above paragraph for details) for each WM performance group. We reported if the shifting points are different for different groups.

To test the effect of age on WM bounds, we fit each age group's data separately to our working memory model (Age group: young, middle-aged, older adult group, n = 53 per each group). We report the posterior distribution of the group-level WM noise parameter ($\varepsilon_{\text{set size}}$: the proportion of the noise in WM policy) for each set size. For statistical inference on whether an older group has lower WM ability than a younger group, we examined if the HDI for the comparison across age groups (at each set size) does not overlap zero.

As a secondary individual differences analysis, we examined the correlation between an individual's age and their average posterior mean of the WM noise estimates across set sizes ($\Sigma_{\text{set size}}(\varepsilon_{i,\text{ set size}})$, i = 1, …, N, set size = 1, 2, …, 6).

Since we confirmed that the older adult group has higher WM noise than the middle-aged adult group (see Results section), we further tested if the older adult group shows earlier shifts from WM to RL than the middle-aged adult group. The procedure was identical to the proposed analyses for the WM capacity groups described above except that we use different age groups here.

To test if the different age groups use bounded optimal WM-RL trade-off, we will compare the estimated $w_{\text{set size}}$ (how much individuals *actually* rely on WM compared to RL) and the bounded optimal $w^*_{\text{set size}}$ (how much individuals *should be* relying on WM compared to RL in order to get maximum reward from the task conditional upon their WM and RL ability). Bounded optimality analysis (Lewis et al., 2014) provides a principled way of asking whether groups use the strategies that will lead to maximum performance in the choice learning task given their bounds in information processing systems (i.e., WM and RL). The first step of this analysis was to measure the bounds/limitations of a cognitive system. We proposed to use an external working memory task and model to measure the set size-specific WM noise for each group. We chose to use set size-specific noise to represent WM limitations on the assumption that adding more items to working memory increases noise (and thus decreases the accuracy and reliability of the system), either because people do not encode larger sets due to limited time, greater inter-item interference in representation and retrieval, or a combination of both (Anderson & Reder, 1999; Oberauer, 2009).

The key assumption in this study was that the set size-specific WM noise is the critical bound that should constrain how individuals should balance WM and RL in the choice learning task. If the WM noise is very high at a certain set size to the extent that WM policy is less accurate than RL policy, participants should shift to relying more on RL. Using the bounds in WM (i.e., set size-specific noise) and RL (i.e., learning rate, softmax beta) estimated for each group, we derived the optimal balance between RL and WM that leads to maximum utility in the choice learning task by simulation. This bounded optimal strategy ($w^*_{\text{set size}}$) was then used for simulating bounded optimal behavior for that group – that is the best possible performance we can expect from this group, given their estimated WM capacity and RL learning rate. For each possible mixture weight value with 0.01 interval (i.e., 0.00, 0.01, 0.02, …, 1.0), we estimated the average accuracy from the 100 simulated experiments. The last step was to compare the bounded optimal prediction with the observed behavior. To the extent that the predicted behavior corresponds to observed behavior, the behavior was explained as bounded optimal.

We report (1) the bounded optimal mixture weight value ($w^*_{\text{set size}}$), (2) the 95% CI of the estimated mixture weight parameter ($w_{\text{set size}}$), (3) the bounded optimal performance, and (4) the observed performance (data). Inference on whether the group used bounded optimal strategies or not can be made by testing if the 95% CI of the estimated mixture weight overlaps with the derived bounded optimal weight. The bounded optimality analysis was conducted (1) on one group including all individuals, (2) separately for different WM performance groups, and (3) separately for different age groups.

Results

Table 4-1. The number of subjects and mean age for each group

	Age group			WMC group		
	Young	Middle age	Old	Low	Med	High
N (female)	53 (28)	53 (34)	53 (28)	53 (26)	53 (32)	53 (32)
Age (SD)	22.5 (1.86)	47.5 (1.78)	72.0 (1.73)	49.0 (21.8)	48.4 (20.1)	44.7 (19.3)

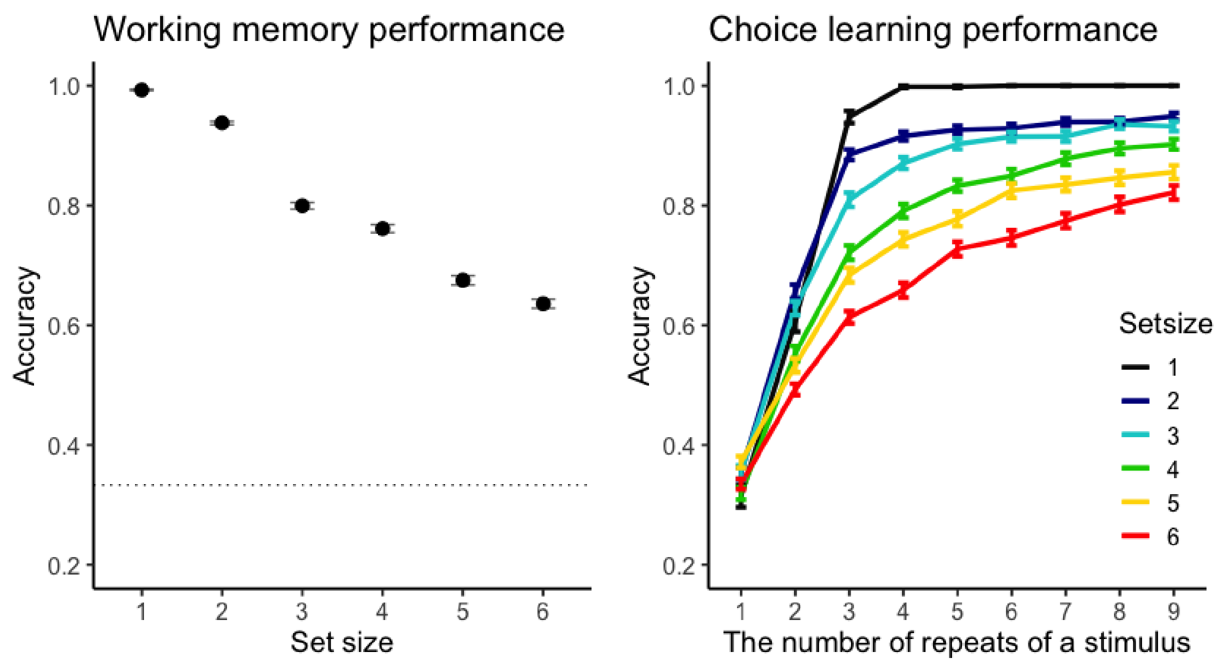
Table 4-2. Posterior mean and 95% CI of the mixture weight parameter at each set size for different populations

		Posterior mean and 95% CI			Difference HDI compared to set size 1 (95% CI)	
	Set size	Mean	Lower CI	Upper CI	Lower CI	Upper CI
All participants						
	1	0.96	0.94	0.98		
	2	0.79	0.75	0.83	0.13	0.22
	3	0.30	0.24	0.37	0.60	0.72
	4	0.21	0.18	0.25	0.70	0.79
	5	0.21	0.17	0.25	0.70	0.79
	6	0.28	0.23	0.32	0.64	0.73
WM capacity groups						
Low						
	1	0.97	0.93	1.00		
	2	0.68	0.58	0.77	0.19	0.39
	3	0.13	0.09	0.17	0.79	0.89
	4	0.19	0.14	0.25	0.71	0.84
	5	0.33	0.27	0.40	0.57	0.72
	6	0.44	0.38	0.51	0.45	0.60
Medium						
	1	0.94	0.90	0.98		
	2	0.78	0.71	0.84	0.09	0.24
	3	0.37	0.28	0.47	0.47	0.68
	4	0.27	0.22	0.33	0.60	0.74
	5	0.26	0.20	0.32	0.62	0.76
	6	0.30	0.23	0.38	0.56	0.73
High						
	1	0.95	0.91	0.98		
	2	0.77	0.71	0.84	0.10	0.25
	3	0.68	0.58	0.78	0.15	0.37
	4	0.31	0.24	0.38	0.56	0.72
	5	0.15	0.11	0.21	0.73	0.86
	6	0.22	0.16	0.29	0.66	0.81
Age groups						
Young adults						
	1	0.96	0.91	0.99		
	2	0.71	0.64	0.78	0.17	0.33
	3	0.39	0.30	0.48	0.47	0.66
	4	0.22	0.16	0.29	0.66	0.81
	5	0.25	0.18	0.32	0.64	0.79
	6	0.20	0.15	0.25	0.69	0.82
Middle age adults						
	1	0.97	0.93	0.99		
	2	0.79	0.73	0.86	0.11	0.25

	3	0.47	0.36	0.58	0.38	0.61
	4	0.25	0.19	0.31	0.65	0.78
	5	0.17	0.12	0.22	0.73	0.85
	6	0.26	0.20	0.32	0.64	0.79
Older adults						
	1	0.95	0.91	0.98		
	2	0.82	0.76	0.89	0.06	0.20
	3	0.12	0.08	0.17	0.77	0.89
	4	0.20	0.15	0.26	0.68	0.81
	5	0.25	0.19	0.32	0.63	0.78
	6	0.41	0.32	0.49	0.46	0.64

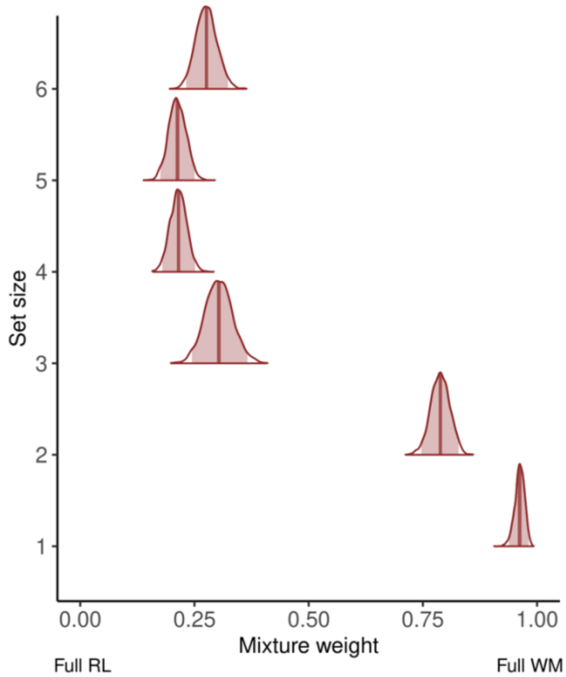
CI: Credible intervals

Figure 4-3. The average accuracy of the working memory task and the choice learning task in all participants



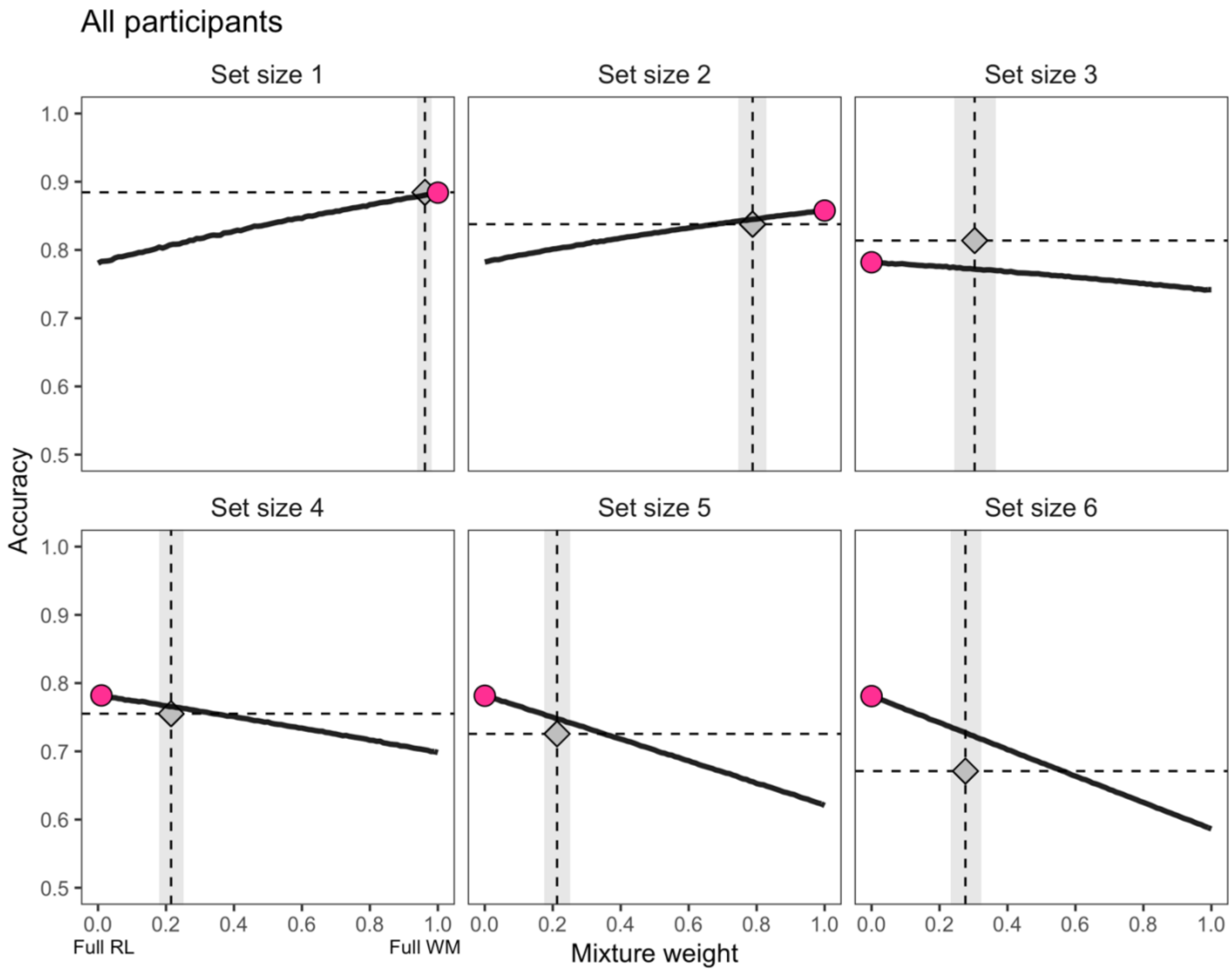
Error bars show standard errors.

Figure 4-4. WM/RL trade-off in all participants



The posterior distributions of the group-level mixture weight parameter (the proportion of reliance on WM as opposed to RL) for each set size. Vertical lines show the mean of the posterior, and the shaded areas show 95% credible intervals.

Figure 4-5. Bounded optimality analysis for all participants



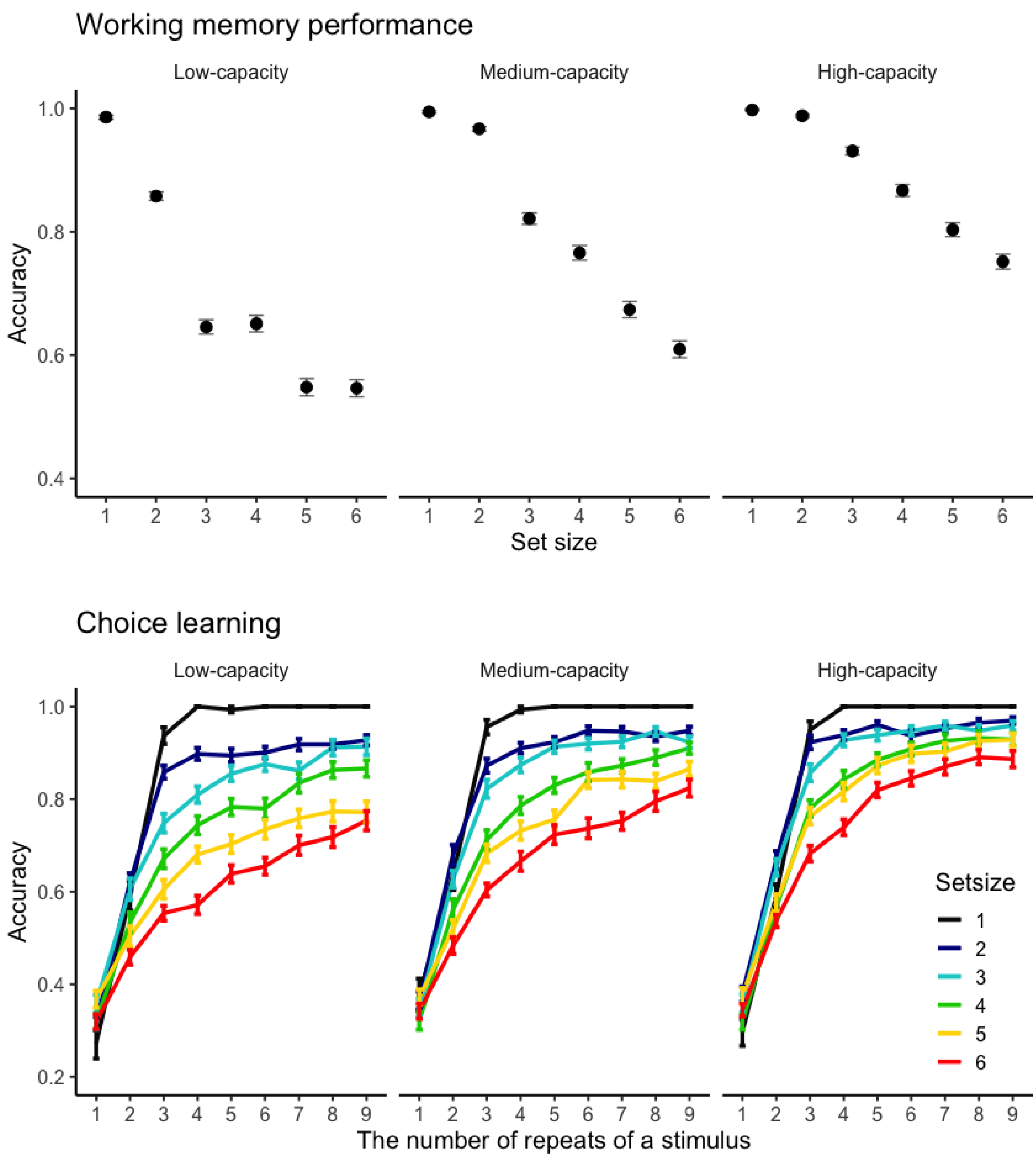
The pink circle indicates performance (y-axis) if using the bounded optimal strategy (x-axis: mixture weight; higher values: more reliance on WM). The grey diamond shows actual performance (y-axis) and empirical estimates of mixture weights (x-axis; shading 95% credible intervals). The thick solid line indicates hypothetical (simulated) performance across possible mixture rates.

All analyses were preregistered. Table 4-1 shows the participants' demographic information, and Figure 4-3 and Supplemental Material S1 show behavioral data in the working memory task and the choice learning task. Our first question concerned whether people (across all groups) adaptively adjust how they combine WM and RL in choice learning and to which extent their combination is bounded optimal. We first fit the trial-level data from the independent working memory task to estimate set size-specific noise for this population. We defined this set-size specific noise to be the WM bounds of this population. As expected, WM noise increased with increasing set sizes (see Supplemental Material S3 and S4 for the posterior distributions and summary of WM bounds).

Importantly, when we estimated the empirical and bounded optimal mixture weights, it was assumed that the WM system had the set size-specific noise bounds we measured from the independent task/model above (the bounds in the RL system were estimated within the choice learning model). In our preregistered analysis plan, we had assumed that the mixture weight at set size 1 would represent full reliance on WM. As shown in Figure 4-4, people shifted away from full reliance on WM at set size 2 (the HDI of the pairwise difference between the mixture weight at set size 1 and all the other set sizes did not contain 0; see Table 4-2 for details). From set size 3, people began to rely more on RL than on WM (i.e., $w < 0.5$; $w_{\text{set size 3}} = 0.30$ [0.24 0.37]).

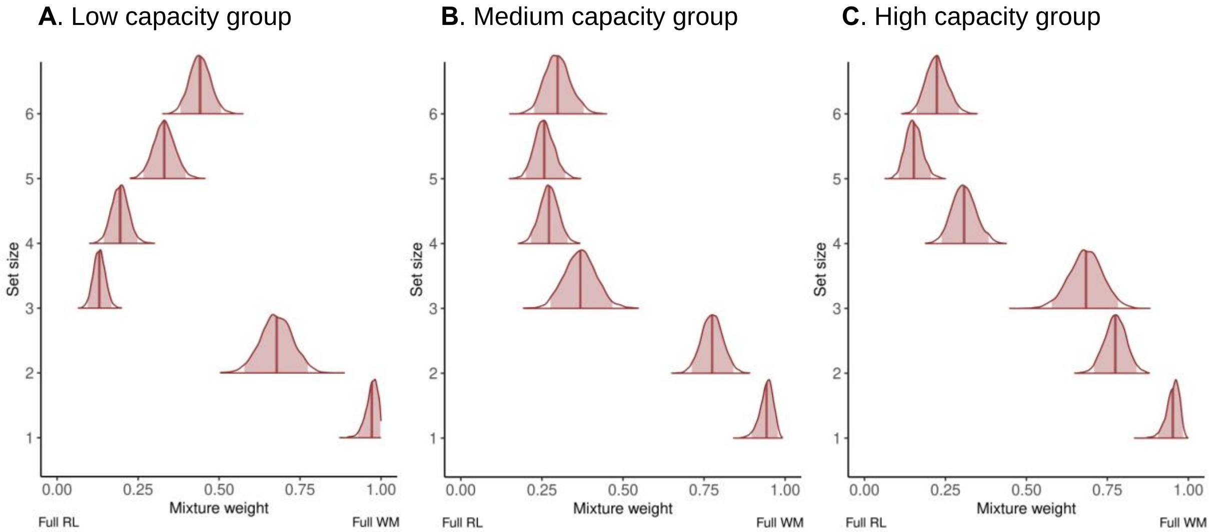
Bounded optimality analysis suggested that such dominance of RL from set size 3 is adaptive as it is optimal given the bounds of this population to fully rely on WM up to set size 2 and fully rely on RL from set size 3 (Figure 4-5). However, except for at set size 1, the degree to which people relied on WM vs. RL was not exactly at the optimal point. Specifically, people started to shift toward RL too early (set size 2) than they should be shifting to get maximum accuracy (set size 3). Moreover, people still utilized WM at set size 3 and above (about 20-30%) even though they could have performed better by relying more on RL, as shown in Figure 4-5. See Supplemental Material S3 for the posterior estimates of all parameters. See Supplemental Material S8 and S9 for robustness and sensitivity checks of the models.

Figure 4-6. The average accuracy of the working memory task and the choice learning task in different working memory capacity groups



Error bars show standard errors.

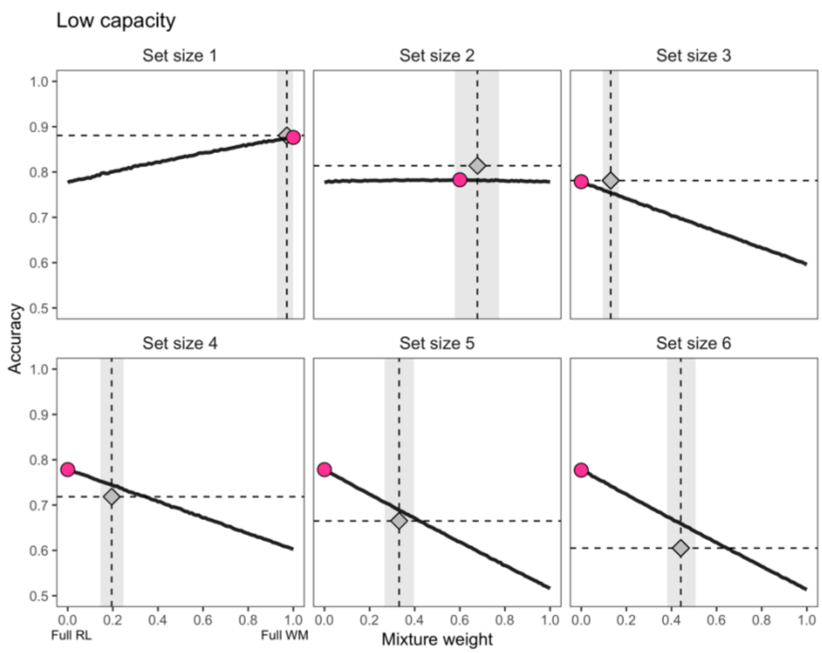
Figure 4-7. WM/RL trade-off in low, medium, high WM capacity groups



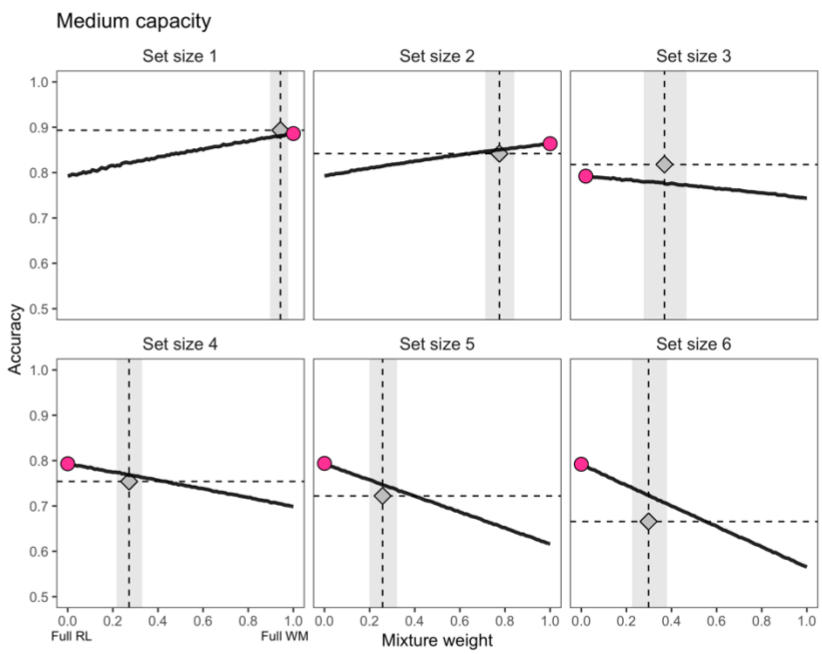
A: Low-capacity group. B: Medium-capacity group. C: High-capacity group. The posterior distributions of the group-level mixture weight parameter (the proportion of reliance on WM as opposed to RL) for each set size. Vertical lines show the mean of the posterior, and the shaded areas show 95% credible intervals.

Figure 4-8. Bounded optimality analysis for low, medium, and high-capacity groups

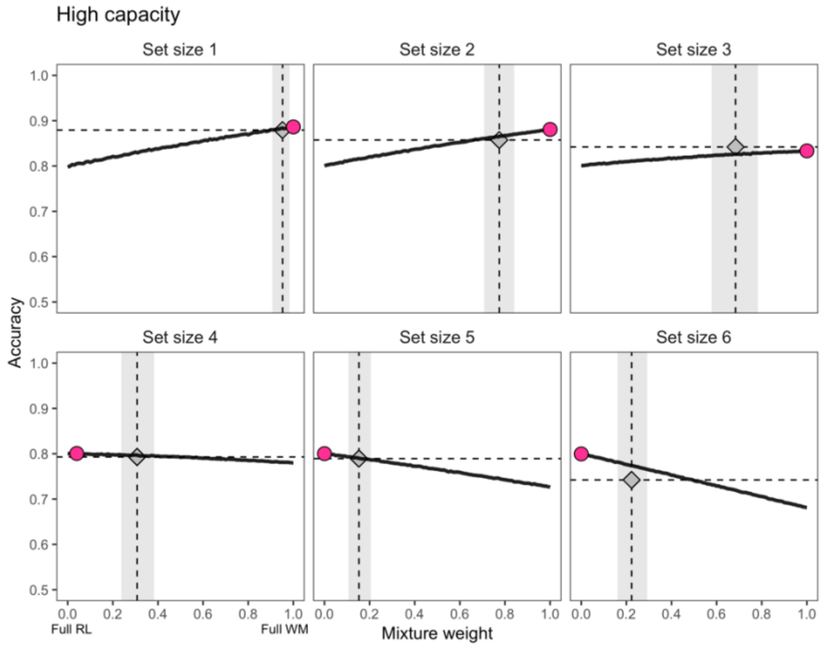
A.



B.



C.



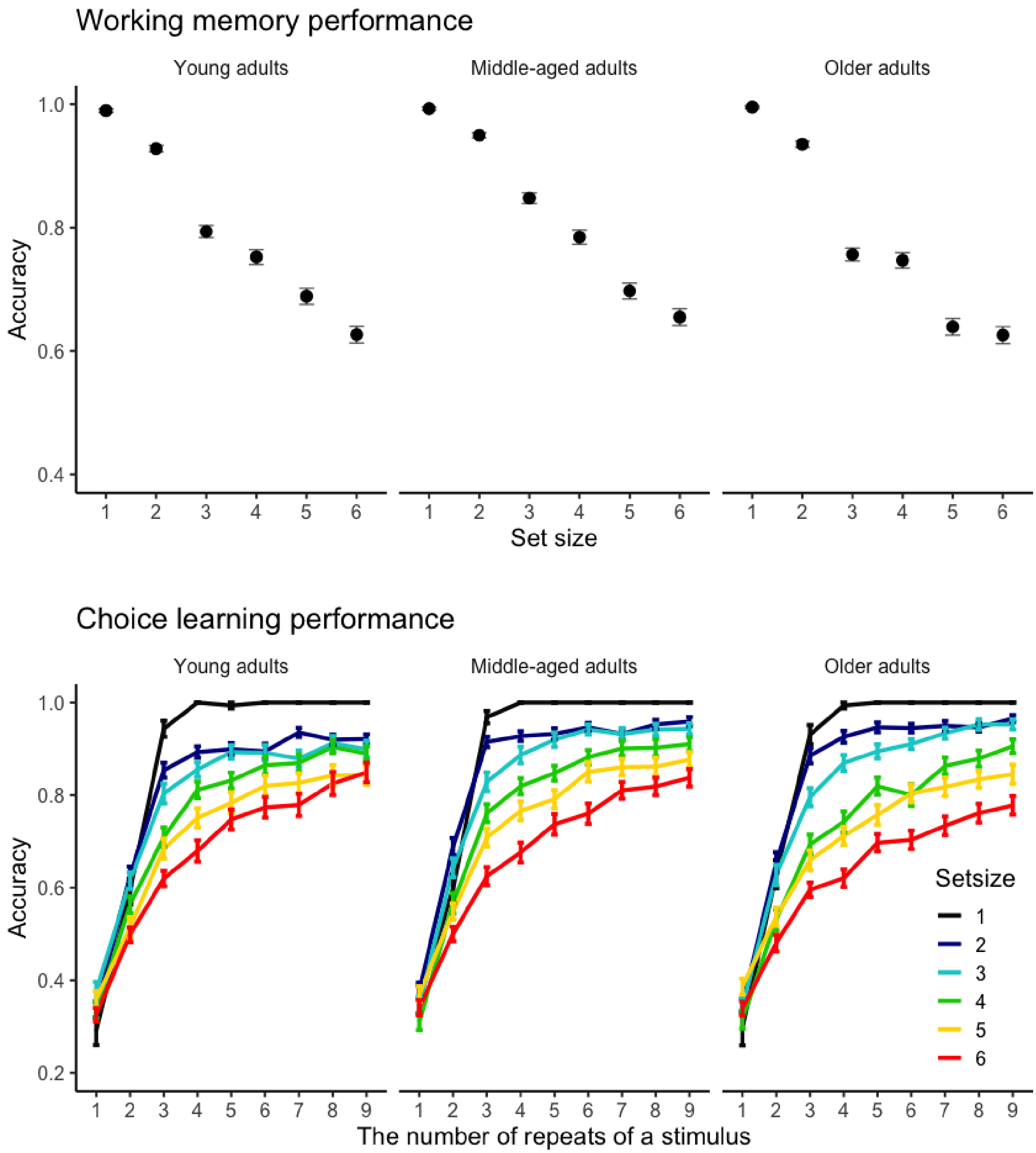
A: Low-capacity group. B: Medium-capacity group. C: High-capacity group. The pink circle indicates performance (y-axis) if using the bounded optimal strategy (x-axis: mixture weight; higher values: more reliance on WM). The grey diamond shows actual performance (y-axis) and empirical estimates of mixture weights (x-axis; shading 95% credible intervals). The thick solid line indicates hypothetical (simulated) performance across possible mixture rates.

Next, we examined how people with different WM bounds varied in how they combined WM and RL and in the extent to which their combination was bounded optimal. We first categorized participants (young, middle-aged, older adults combined) into the low-, medium-, and high-capacity groups using their average behavioral performance in the working memory task (Figure 4-6, Supplemental Material S3). There was no significant association between the working memory capacity group and the age group (chi-square = 5.55, $p = 0.24$; see Supplemental Material S2 for the contingency table of the capacity group and the age group). We then measured the specific WM bounds of the different capacity groups by fitting the working memory model. As expected, WM noise increased with increasing set size for all groups, and the high-capacity group had the lowest WM noise overall (see Supplemental Material S3 and S5 for the posterior distributions and summary of WM bounds in each capacity group).

We then estimated each group's empirical and bounded optimal mixture weights with the assumption that the WM system had the set size-specific noise bounds estimated above. As shown in Figure 4-7, all groups shifted away from full reliance on WM at set size 2 (the HDI of the pairwise difference between the mixture weight at set size 1 and all the other set sizes did not contain 0; see Table 4-2 for details). In terms of when RL becomes dominant, the low- and medium-capacity groups started to rely more on RL than WM (i.e., $w < 0.5$) from set size 3, whereas it was not until set size 4 that the high-capacity group started relying more on RL than WM (see Table 4-2 for details).

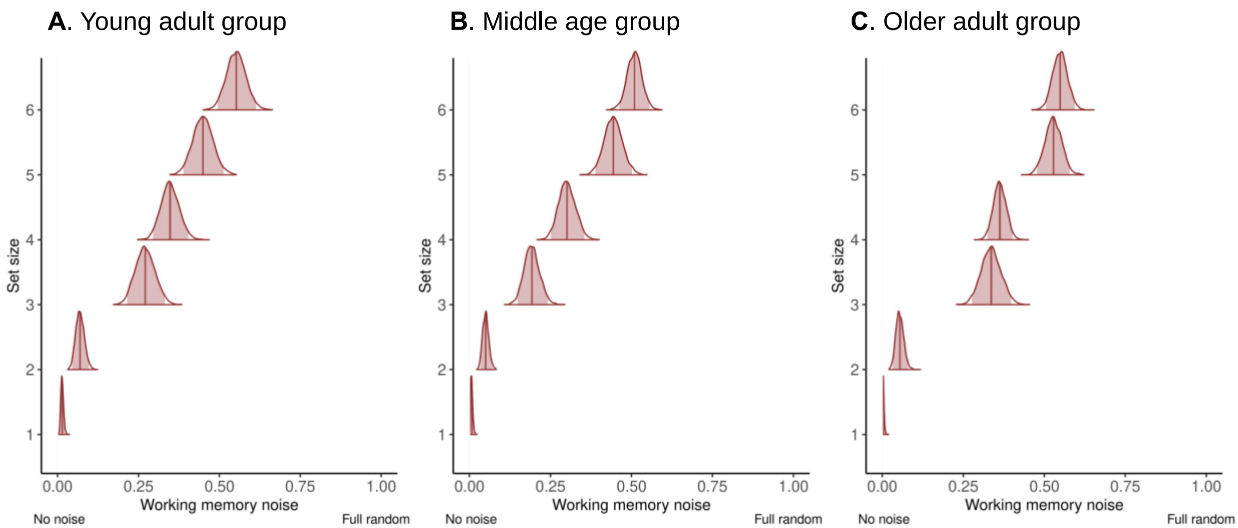
Variation in the set size point at which RL becomes more dominant than WM in different capacity groups could be, in part, explained by the variations in the bounded optimal mixture weights in different capacity groups. That is, for the low- and medium-capacity groups, it was optimal to move away from full reliance on WM from set size 3; whereas, for the high-capacity group, that shifting point was from set size 4. However, the results indicate that behavior was not strictly bounded optimal as defined by the model: Except for set size 1, all groups showed some gap between the estimated mixture weights and the strictly optimal mixture weights. Overall, all groups tended to over-rely on WM even when they could have performed better by relying fully on RL, especially at set sizes 4 to 6. The low-capacity group showed the most significant gap between the optimal mixture and empirical mixture weights, especially at the largest set size. This suggests that the low-capacity group could have performed better in the task by relying fully on RL at higher set sizes (e.g., at set size 6, the actual performance was 0.60 in the accuracy, but the predicted performance when using bounded optimal weight was 0.78 in the accuracy). It is also worth noting that, in some cases, different combinations of WM and RL had little impact on the (predicted) performance (e.g., set size 2 in the low-capacity group and set size 4 in the high-capacity group; Figure 4-8). See Supplemental Material S8 and S9 for robustness and sensitivity checks of the models.

Figure 4-9. The average accuracy of the working memory task and the choice learning task in different age groups



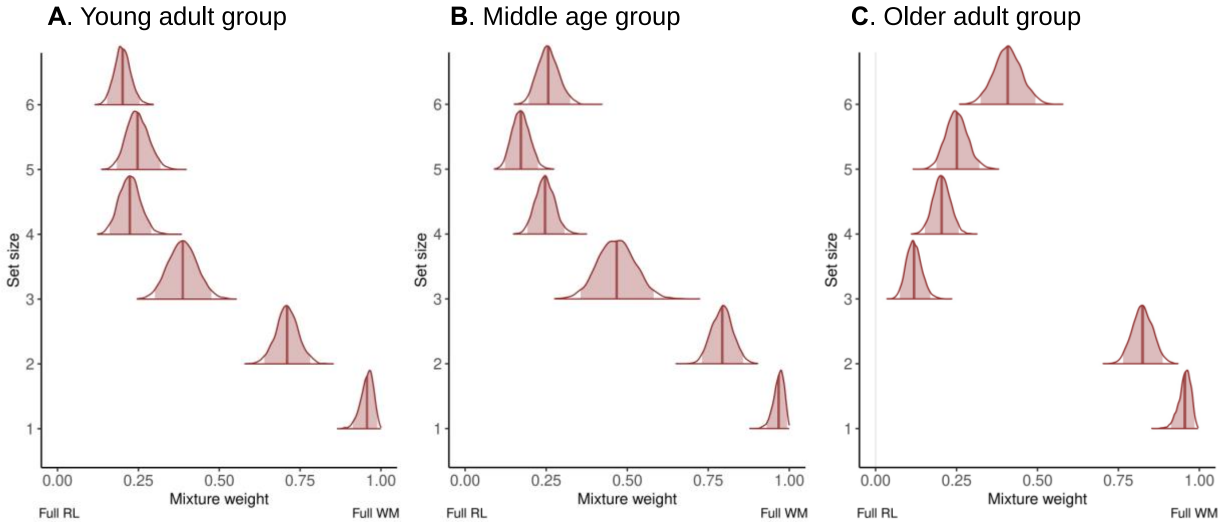
Error bars show standard errors.

Figure 4-10. WM bounds in young, middle age, older adult groups



A: Young adults. B: Middle-aged adults. C: Older adults. The posterior distributions of the group-level working memory noise parameter for each set size (0 = no noise, 1 = full random). Vertical lines show the mean of the posterior, and the shaded areas show 95% credible intervals.

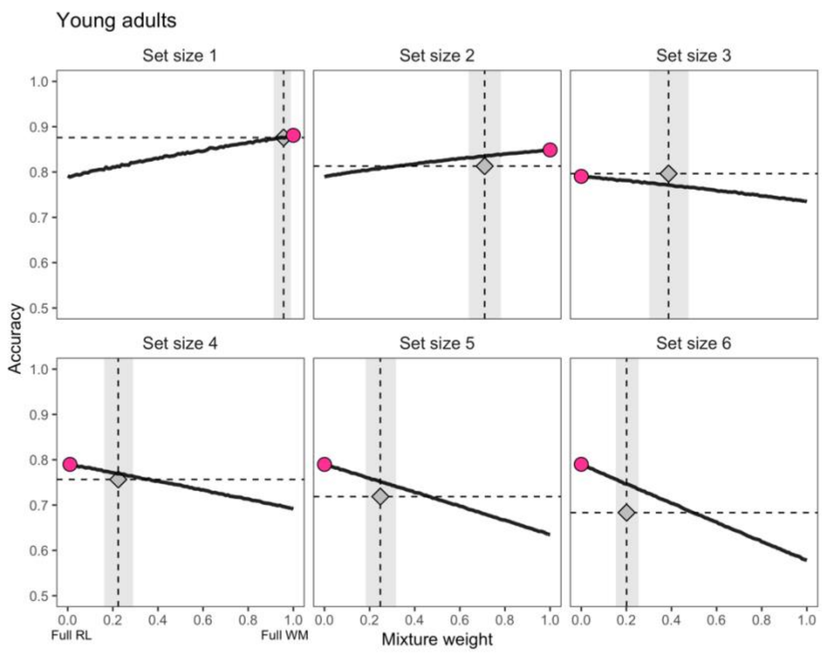
Figure 4-11. WM/RL trade-off in young, middle age, older adult groups



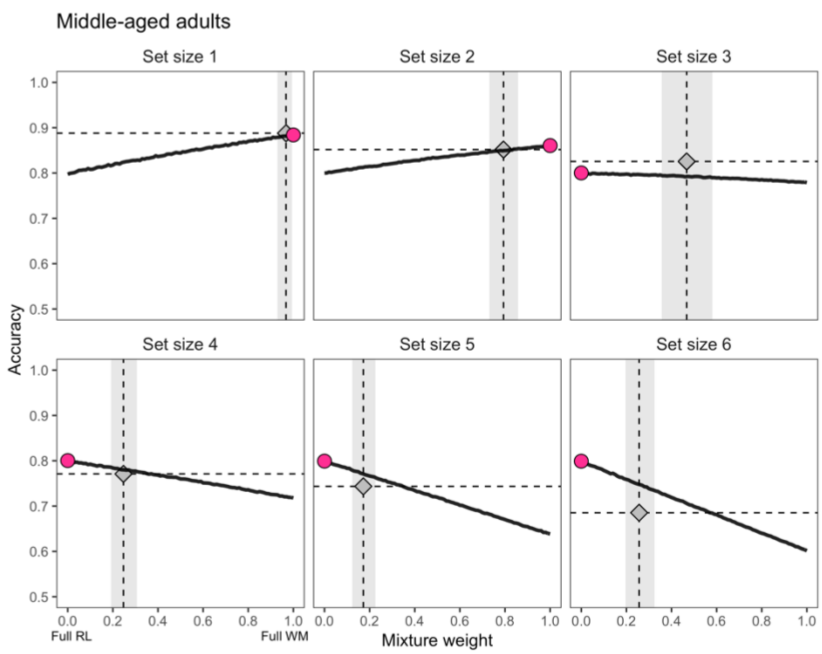
A: Young adults. B: Middle-aged adults. C: Older adults. The posterior distributions of the group-level mixture weight parameter (the proportion of reliance on WM as opposed to RL) for each set size. Vertical lines show the mean of the posterior, and the shaded areas show 95% credible intervals.

Figure 4-12. Bounded optimality analysis for young, middle-aged, older adults

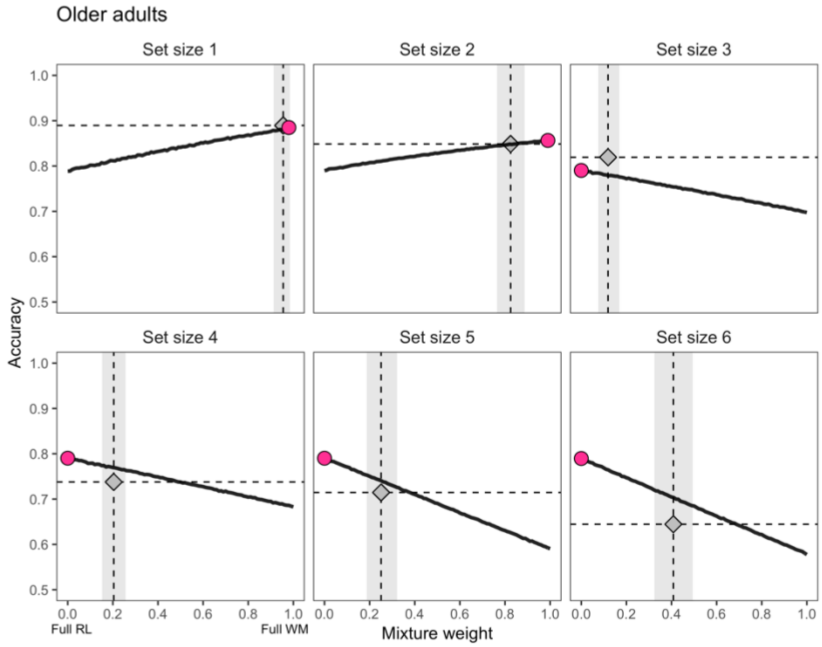
A.



B.



C.



A: Young adults. B: Middle-aged adults. C: Older adults. The pink circle indicates performance (y-axis) if using the bounded optimal strategy (x-axis: mixture weight; higher values: more reliance on WM). The grey diamond shows actual performance (y-axis) and empirical estimates of mixture weights (x-axis; shading 95% CI). The thick solid line indicates hypothetical (simulated) performance across possible mixture rates.

Lastly, we examined (1) whether people of different ages have different levels of WM bounds and, (2) if so, whether they vary in how they combined WM and RL and in the extent to which their combination was bounded optimal. Figure 4-9 and Supplementary Material S1 show the behavioral data for each age group. We initially hypothesized that working memory ability will be highest in the young adult group and the lowest in the older adult group. However, the young and older adults did not differ in performance on the working memory task (regression coefficient $\beta_{\text{Young vs. Old}} = -0.01$, $p = 0.46$). Only middle-aged adults and older adults showed a significant difference in working memory performance (older adults performing slightly worse than middle-aged adults; regression coefficient $\beta_{\text{Middle-age vs. Old}} = -0.04$, $p = 0.02$). Next, we fit each age group's data to the working memory model to estimate set-size specific noise in WM. Figure 4-10 shows the posterior distributions of the set size-specific noise in working memory for each age group. Comparison of the HDI of the WM noise between age groups at each set size suggested that the older adult group had higher WM noise than the middle-aged group in set sizes 3, 4, and 5 (see Supplemental Material S6 for the difference HDI between groups). Correlation between individuals' age and WM noise (average across set size) was not significant (Pearson $r = 0.12$, $p = 0.13$; see Supplemental Material S7 for the scatter plot).

Since the older adult group had higher set size-specific WM noise than the middle-aged group, especially at set sizes 3 to 5, we further tested if the older adult group showed earlier shifts from WM to RL compared to the middle-aged group. All groups started to move away from full reliance on WM at set size 2 (see Table 4-2 for the difference in HDI of mixture weights between set size 1 and other set sizes). The older adult group (and the young adult group) started to rely more on RL than WM (i.e., $w < 0.5$) at set size 3; whereas it was not until set size 4 that the middle-aged adult group started relying more on RL than WM (Figure 4-11, Table 4-2).

As shown in Figure 4-12, the bounded optimal strategy for all groups would have been to entirely rely on WM up to set size 2 and entirely rely on RL from set size 3. However, except for set size 1, all age groups showed some gap between the bounded optimal mixture weights and the empirical mixture weights. Specifically, there was an overall tendency of over-reliance on WM in all age groups. Moreover, older adults showed the most significant gap between the optimal mixture and empirical mixture weights, especially at the largest set size. This suggests that older adults could have performed better in the task by relying more strongly on RL than using their WM (e.g., at set size 6, the actual performance was 0.63 in the accuracy, but the predicted performance when using bounded optimal weight was 0.78 in the accuracy). See Supplemental Material S8 and S9 for robustness and sensitivity checks of the models.

Discussion

In this study, we examined how people balance their use of WM vs. RL processes in a choice learning task in accordance with their own abilities and the task demands. Interestingly, although people were adaptive in how they shifted from relying on WM vs. RL – that is, they decreased reliance on WM and increased reliance on RL as the WM load of the task increased, they did not strictly follow the pattern suggested by bounded optimality.

One of the main questions in this study was whether people adapt to their own bounds and whether there are differences in these adaptations in people with different cognitive abilities and ages. To answer this question, we conducted a bounded optimality analysis on groups with different WM capacities, groups with different ages, as well as all subjects from all groups. Across these analyses in different populations, we found that people adapt to their own bounds, but they are not strictly bounded optimal as defined by the model. When the task load was minimum, people fully relied on WM in choice learning. As the task load increased, people began to increase reliance on RL and decrease reliance on WM. The point at which RL became more dominant than WM varied for different capacity groups and age groups. This variation in when RL becomes dominant in different groups, in part, reflected their bounded optimal mixture strategies. People shifted to the RL-dominant strategy in set size points at which the bounded optimal weight changed from full reliance on WM to full reliance RL (in most cases, the bounded optimal weights were either 1 (full reliance on WM) or 0 (full reliance on RL)).

Even though the point at which people shifted to the RL dominant strategy was consistent with bounded optimality, people were not strictly bounded optimal in that the credible intervals of the posterior distributions of the mixture weights did not overlap with the bounded optimal weights, except for set size 1. First, people shifted too early: In lower set sizes where bounded optimal strategy was a full reliance on WM, people over-relied on RL when they hypothetically could have done better by engaging more WM. On the one hand, this might be explained by the fact that using WM is effortful (Westbrook et al., 2013), and those costs may lead people not to engage it as fully as they might if they are not very motivated (Dunn et al., 2016; Kool et al., 2010). As mentioned in the Introduction, behavior results from the integration of stable traits, situational demand, and the cognitive-emotional states of individuals. The current study considered the first two factors: we measured stable traits, namely the cognitive limitations in WM and RL, and examined the effects of situational demand by manipulating task load (set sizes). However, our analysis did not address the effects of the cognitive-emotional state. It remains an interesting question whether the differences in the costs of working memory and other emotional/motivational factors might help explain the over-reliance on RL at lower set sizes.

In contrast to the over-reliance on RL at lower set sizes, there was an opposite pattern in the higher set sizes: people over-relied on WM when it was optimal to fully rely on RL given that the task load exceeds their WM capacity. This pattern of over-reliance on WM was especially strong for the people with low WM capacity and the older adults. An interesting question related to this is whether the underlying mechanism is similar or different for the low-capacity individuals and the older adults. One conclusion we might draw from these results is that older adults don't adapt as well as they could, but that might not be the correct conclusion; maybe it is the low WM capacity that explains the poor adaptation regardless of age group. Although an explicit test of the interaction between WM capacity and age is necessary to understand a complete picture, the fact that (1) we had an even distribution of age groups in each WM capacity group and (2) there was no significant association between the individual age and

WM bounds suggests that both lower capacity and older age could be predictors of the gap between the optimal and empirical mixture weights. Though this lack of age differences in WM in our sample was informative in this aspect, it can be considered a limitation since this is not consistent with the well-known age-related decline in WM (Borella et al., 2008; Nilsson, 2003; Old & Naveh-Benjamin, 2008; Spencer & Raz, 1995; Verhaeghen et al., 1993; Wingfield et al., 1988) and raises a question about the representativeness of older adults on online data collection platforms (Greene & Naveh-Benjamin, 2022; Vroman et al., 2015).

Moreover, the low-capacity individuals and older adults showed a curvilinear pattern in the mixture weights as a function of set size. That is, they increased reliance on RL as set size increased from 1 to 3, but they reversed the pattern and shifted back towards increased reliance on WM as set size increased from set size 4 to 6. What might explain this regression to WM at higher set sizes? One possible explanation is that people tried to ramp up cognitive effort to compensate for low performance at higher set sizes. A similar finding in aging literature suggests that older adults apply more top-down, controlled processing when their automatic processing is not successful in accomplishing the task goal (Staub et al., 2014, 2015). A different explanation is that people started to use a different strategy that relies more on WM at higher set sizes. For example, they might have decided to focus on either just the first or most recent items in the presented set once they realize the set size is going to be large. Alternatively, it might be that the set size 3 (or 4) is a breakpoint where the capacity of working memory per se has been exceeded and long-term memory processes come more into play (Cowan, 2001).

It is also worth noting that, in some cases, different combinations of WM and RL had little impact on the predicted performance. For example, for the low-capacity individuals, the predicted performance line as a function of hypothetical mixture weights was flat in set size 2. In this situation, using different strategies will not make a difference in performance. Being able to identify this kind of situation is one of the strengths of conducting the bounded optimality analysis. This will be especially valuable when designing an intervention that targets different cognitive strategies because it allows one to precisely quantify how much increase in performance (or utility) one can expect from a change in cognitive strategies in a task.

It is also possible that deviations from what the model defines as "bounded optimal" could result from limitations in the modeling. First, some of the assumptions made in our computation model might need to be revisited. Our model assumed that the working memory and reinforcement learning systems are independent, and they have a competitive relationship (in that an increase in reliance on one system means a decrease in reliance on the other system). Even though our models showed good sensitivity in predicting the behavior data and were robust in replicating the trend in a separate pilot dataset (Supplemental Material S8 and S9), recent studies suggest a more complicated and interactive nature of working memory and reinforcement learning integration (Collins, 2018; Yoo & Collins, 2022). For example, Collins (2018) showed that WM could influence RL computations by providing information for the calculation of the reward prediction error. It will be important in future work to compare the bounded optimality predictions in different models of the WM and RL integration and to examine if they lead to different conclusions about the adaptation to cognitive bounds.

In the Introduction, we stressed the importance of situational demand (task demand) in behavior. The current study focused on the effects of task load on the adaptive nature of WM and RL integration. In addition to task load, other task-related factors can pose important implications in adaptive strategies in choice learning. For example, the length of the task (i.e., the number of trials) can affect bounded optimal mixture weights in choice learning. As the number of total trials in a task decrease, it would be better to use WM because WM learns faster than RL; as the number of trials in the task increases, it would be better to use RL because RL is more robust to interference than WM. Another example is the delay between repetition of the stimulus (e.g., spaced vs. massed). If the stimuli are repeated after a long delay, it would be better to use RL; if the stimuli are repeated after a short delay, it would be better to use WM (see Wimmer & Poldrack (2022) for related discussion).

Another critical question to be explored is the development of adaptation with experiences (i.e., do people move close to an optimal strategy as they experience more trials in the task?). The current study estimated a single mixture weight across all trials in each set size—therefore can only speak about the overall strategy; however, future work would better explain the changes in adaptations by (1) estimating the mixture weights as a function of trials in the task and (2) examining if the gap between the bounded optimal and empirical weights reduces with more trials. The prediction is that people might get closer to an optimal strategy with experiences since learning is required to achieve optimality. Other future directions might include leveraging different methodologies to aid a fuller understanding of the adaptive nature of WM and RL integration. For example, neural signatures of different utilization of WM (Rottschy et al., 2012) could be used to recover the WM and RL integration on both neural and behavioral levels, and pupillometry measures could be used to understand how motivational factors are related to the integration of automatic RL and effortful WM processes in choice learning.

Although these other questions remain to be explored, the current study contributes to understanding the adaptive nature of WM and RL integration in choice learning in groups with different abilities and ages. We suggested a novel way to measure WM bounds using an independent task and model, as well as a way to define computationally rational strategy using the modified version of Collins & Frank’s computation model of choice learning with a bounded optimality assumption (Lewis et al., 2014). Our finding suggest that people are overall adaptive, but not computationally optimal, in how they balance WM and RL. Even more interesting, people seem to paradoxically increase reliance on WM at the highest set sizes, when it is least reliable, and this especially true for individuals with lower working memory performance and older adults. Going forward, future studies to better understand why people differ from strategies that are hypothetically optimal – and especially why they may engage effortful WM processes more than they “should” – may be helpful for designing interventions and environments that help people optimize their performance.

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Supplemental Material

The Supplemental Material for this chapter can be found online at: https://osf.io/6qwru/

Chapter 5 General Discussion

The Adaptive Use of Working Memory in Response to Loss Incentives

Summary of Findings

Working memory demands are common in everyday life. Failure to meet those demands can lead to losses, especially for older adults. Different theories in the literature make different predictions for how older adults may respond to loss incentives: Motivational shift theory suggests that older adults are especially motivated to avoid losses (Freund & Ebner, 2005), some interpretations of the age-related positivity effect suggest that older adults may ignore losses (Brassen et al., 2012; Williams et al., 2017), and yet another set of views suggests that losses might differentially disrupt older adults (Charles, 2010; Hess, 2014). Studies 1 and 2 (Chapters 2 and 3) contribute to our understanding of how loss incentives affect young and older adults' working memory and motivation across different tasks.

Study 1 used a working memory task that required participants to view a sequence of random numbers and letters and then immediately recite the numbers in numerical order, the letters in alphabetical order. Contrary to our initial hypothesis and previous findings in our lab (Lin, 2018; Lin et al., 2019) that loss would have a negative impact on older adults' cognitive performance, loss incentive did not affect working memory performance for either age group. Instead, for both age groups, loss incentive increased subjective feelings of mental demand and frustration, especially at the highest set sizes. However, other aspects of the data suggest that these increases in perceived demand and frustration may have occurred for different reasons in young and older adults, as the self-report data indicate that young adults found the losses to be distracting, whereas older adults found them de-motivating.

In trying to understand why loss incentive effects are sometimes expressed in terms of performance (Lin, 2018; Lin et al., 2019) and at other times in feelings of demands (Study1; Jang et al., 2020), we considered that one possibility might be that the task used by Lin et al. was very open-ended and provided ample opportunities to disengage attention from the task. (Indeed, the task is designed to make it difficult to sustain attention and engagement.) In contrast, the working memory task used in Study 1 of the current dissertation was relatively fast-paced and required participants to speak to the experimenter on every trial. In Study 1, these task constraints may have kept people engaged in the task even when motivation was decreased.

Study 2, therefore, used a Sternberg-type working memory task. On each trial of each task, participants silently viewed a set of letters, followed by a retention interval with just a fixation cross on the screen, and then were presented with a probe item and pressed one key to indicate that it was a member of the memory set, another to indicate that it was not. As this task does not require the same kind of interaction with the experimenter on each trial and has a retention interval that may further encourage attention to drift from the task, remaining engaged with and focused on the task itself may require more self-initiated processing than the relatively active task used in Study 1. Here, consistent with our hypotheses, we found that loss incentive increased young adults' motivation and working memory performance, with opposite effects for older adults. Providing additional support for the idea that incentive affected the degree to which people were engaged in the task, diffusion modeling analysis identified drift rate, a measure of the quality of the memory representation, as the primary locus of these effects rather than strategic bias, speed-accuracy tradeoffs, or nondecision processes (e.g., overall motor speed).

Specifically, the effects on drift rate suggest that the incentive may have influenced how much effort participants put into forming or maintaining the memory representation.

Implications

Taken together, our results in the first two studies (Chapters 2 and 3) suggest that loss incentive, especially when consistently delivered, can lead to a loss of motivation in older adults. Whether that loss is expressed in terms of performance or in subjective feelings of demands may depend on situational factors, including the structure of the task. In tasks with features that may help keep participants engaged in the task even if their motivation is low, performance may not differ between groups., but those with lower motivation may find it more subjectively demanding. The opposite might be true in less-constrained tasks, such as that used in Study 2, where less-motivated participants can escape increased perceived demand by reducing their performance.

The idea that task constraints may determine whether increases and decreases in motivation are primarily expressed in subjective responses vs. performance seems most consistent with the theoretical perspectives emphasizing the importance of engagement (Hess et al., 2016). Considering situational factors and task variables suggests another interesting possibility: Rather than taking a “winner take all” approach to the different theoretical perspectives on aging and motivation, and especially the response to losses, it may be more helpful to consider under which conditions each is most likely to apply. For example, motivational shift theory suggests that while young adults are more motivated to achieve gains, older adults are more motivated to avoid losses (Best & Freund, 2018). This view may be especially relevant for how older adults prioritize tasks and goals, especially when there are competing options. The age-related positivity effect is the tendency of older adults to direct attention and memory away from negative information, presumably in the service of maintaining a positive emotional state (Carstensen & DeLiema, 2018; Reed & Carstensen, 2012). This perspective seems most applicable to characterizing older adults' reduced responses to loss-incentive cues in reinforcement learning and performance studies. At the cue stage, the negativity associated with losses is still hypothetical and abstract, making it potentially easier for older adults to ignore. However, as our results show, when the loss is actually experienced, older adults are just as, or even more, reactive than young adults (Bowen et al., 2019; Kircanski et al., 2018; Samanez-Larkin & Knutson, 2015). Reactivity to negative self-relevant information at the outcome stage may impair performance and reduce motivation or lead older adults to disengage from those negative emotions (Barber et al., 2015).

Limitations and Future Directions

Limitations of the current studies include the cross-sectional age group comparison, the difference between the laboratory tasks and real-world situations, and the question of whether monetary incentives have a similar relevance to young and older adults. However, these limitations are prevalent in almost all studies in this domain. It is interesting to note that the results from the Sternberg task (Study 2), which may more closely resemble real-world situations that require goal-driven, self-initiated processing to stay engaged on a task, seem to more closely follow studies occurring in more real-world environments (e.g., job performance, financial planning, etc.; Birdi & Zapf, 1997; Kiso & Hershey, 2017; Persoskie et al., 2014). That said, it is important to note that we did not make a direct comparison of incentive effects on two tasks that are identical except for the features that can manipulate the degree to which the task engages (or constrains) attention in a more bottom-up or reactive way.

One major difference from previous work on aging and incentive effects is that we focused on loss rather than gain. On the one hand, this limits the degree to which our results can be compared to the prior literature, which has focused primarily on gain incentives. On the other hand, this could also be seen as a strength and novel contribution, as our studies begin to fill in that gap. Moreover, as discussed in detail in Study 1, losses are theoretically more incisive than gains due to competing predictions from different perspectives on age differences on motivation. Another difference from many studies of incentive effects on cognitive performance is that we used a session-wide, between-subjects incentive manipulation. In contrast, most recent studies use a trial-wise, within-subjects manipulation. Those within-subjects designs are more efficient but potentially reduce generalization to real-world performance, and there is increasing evidence for the carryover and incentive-context effects that distort estimates of trial-specific effects (Jimura et al., 2010; Schmitt et al., 2017; Thurm et al., 2018).

In short, there are a number of important parameters that could affect whether and how incentives affect motivation, performance, or both in young and older adults. There is a great deal of work to be done to understand the impact of each of those parameters and even more to understand their potential interactions. The studies presented here have complementary strengths and weaknesses compared to the majority of the literature. While they certainly do not provide a complete understanding of the factors influencing age differences in motivation-cognition interactions, they demonstrate the dangers of over-generalizing from the prior literature and encourage a careful and systematic exploration of this parameter space both in the lab and in everyday life.

The Adaptive Use of Working Memory in Choice Learning

Summary of Findings

As we examined in Study 1 and Study 2, people may change their performance in response to costs and benefits; however, it is less known whether people are doing so adaptively or optimally. Study 3 explored the adaptive nature of combining working memory (WM) and reinforcement learning (RL) in response to varying task loads in a choice learning task. We specifically compared the empirical vs. optimal combination of WM and RL using a bounded optimality analysis (Lewis et al., 2014) – a computational framework for deriving strategies that are rational given the specific cognitive limitations of the individual performing the task. We found that although people were adaptive in how they shifted from relying on WM vs. RL – that is, they decreased reliance on WM and increased reliance on RL as the task load increased, they did not follow the pattern suggested by bounded optimality. In low task-load conditions when it would have been optimal from a computational perspective to fully rely on WM, people over-relied on RL. On the other hand, when task load increased to the point that fully relying on RL was the optimal strategy, people over-relied on WM. This gap between the optimal and empirical strategies was especially large for older adults and people with low WM capacity.

Implications

Our main conclusion in Study 3 was that people are not bounded optimal. When the task load was low, people over-relied on RL compared to the predictions of bounded optimality. This could be explained by WM being more effortful, and those costs may have led people not to engage it as fully as they might if they were not very motivated. This suggests the importance of considering cognitive-emotional states and the subjective costs of cognitive effort in optimality analysis. When the task load was high, people over-relied on WM compared to the predictions of bounded optimality. In other words, when the task demands exceeded one's WM capacity and performance declined, people, especially low-capacity people and older adults, started to use more effortful WM even though the optimal strategy is to rely fully on RL. Although further studies are required to aid correct interpretation, this over-reliance on WM at higher set sizes might reflect compensation mechanisms in response to decreasing performance in the task. For example, this might reflect people were increasing cognitive effort and/or utilizing a strategy that relies more on WM (e.g., remembering either the first or most recent items).

Limitations and Future Directions

The current study used a modified version of Collins & Frank's computation model (Collins & Frank, 2012) for understanding the adaptive combination of WM and RL in choice learning. The fact that we used a computation model is one of the primary strengths of the paper because it offers well-defined computationally rational strategies and quantitative predictions about how behavior might differ depending on which strategy is being used. However, at the same time, the use of computation models brings an inherent limitation. This is related to a famous quote by statistician George Box that "All models are wrong, but some are useful." We have aimed to improve the original Collins & Frank model by explicitly measuring the WM bounds and modifying the WM component of the model to better represent the bounds by estimating set size-specific noise in WM. However, we acknowledge that improvements can be made to our model as well. In addition to incorporating subjective costs/benefits into the model, the WM component can be refined by making the mechanisms of the model consistent with dominant working memory theories (e.g., Jonides et al., 2008; Oberauer, 2009). Moreover, it will be important for future work to compare the bounded optimality predictions in different models of WM and RL integration (e.g., are they completely separate, or can one system learn from feedback to responses largely driven by the other system) and examine if different models lead to different conclusions about people's adaptation to cognitive bounds.

Closing Remarks

WM is costly, and people may change their engagement of working memory in response to the costs and benefits of the task. The current dissertation examined the effects of loss incentives and task loads on the use of working memory. Our work suggests that loss incentives increase the perceived costs of performance in young and (more so in) older adults, leading to disengagement of working memory and the subsequent performance drop especially when the engagement is driven by self-initiated control. We also found that people were adaptive, but not strictly bounded optimal, in shifting the balance between working memory and reinforcement learning in response to varying task loads. These results reflect the complicated nature of interactions between internal and external factors such as ability, motivation, and environment in driving performance and engagement in the task. We hope that the current work contributes to our understanding of the adaptive use of working memory and provides useful directions for future research.

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