Opposite reactions to loss incentive by young and older adults: Insights from diffusion modeling

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ABSTRACT

The prospect of loss becomes more salient in later life, and the opportunity to avoid loss is often used to motivate older adults. We examined the effect of loss incentive on working memory in young and older adults. Diffusion-modeling analyses, manipulation of task parameters, and self-report measures identified which aspects of cognitive-motivational processing were most affected within each group. As predicted, loss incentive increased working memory performance and self-reported motivation in young adults, but, consistent with prior work, had the opposite effect in older adults. Diffusion-modeling analyses suggested the primary effect was on the quality of the memory representation (drift rate). Incentive did not interact with retention interval or the number of items in the memory set. Instead, longer retention intervals led to better performance, potentially by improved differentiation between studied items and the unstudied probe as a function of temporal context. Overall, the results do not support theories suggesting that older adults are either more motivated by loss or that they ignore it. Instead, the loss incentive increased young adults' performance and subjective motivation, with opposite effects for older adults. The specific impact on drift rate and lack of interactions with set size or retention interval suggest that rather than affecting load-dependent or strategic processes, the effects occur at a relatively global level related to overall task engagement.

Keywords: working memory, incentive, motivation, diffusion model, cognitive aging

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 et al., 2007), 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.

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 controlled, effortful, strategic process (see reviews by Carstensen & DeLiema, 2018 and Reed & Carstensen, 2012). 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).[1] 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).

The discrepant findings of laboratory versus 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.

[1] Like "attention", the term "engagement" has been used in different ways across the literature. For example, Hess often uses it interchangeably with "effort". We separate those concepts and 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.

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. 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 trialwise 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 as well as remembering the sentence-final word, and did not find differential effects of gain or loss unless a stereotype-threat manipulation was also introduced (there was no young adult comparison group). A previous study from our lab 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 –literally engaging with the experimenter on every trial (Jang et al., 2020). 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 by 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 trialwise 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.

METHODS

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 1 for demographics, Supplementary Materials S15 for exclusion data. 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. 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).

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 section for completeness (Supplementary Materials S16-S21).

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).

Analyses were conducted in the probabilistic programming language Stan (Carpenter et al., 2017; Stan Development Team, 2018) using the wrapper package brms (Bürkner & Buerkner, 2016) 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 & Buerkner, 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. Regarding regression coefficients, k - 1 parameters are estimated for each factor with k levels. For example, the set size factor has three levels and therefore has two contrast coefficients, β_{SS1} (testing the difference between set size 6 vs. set size 8) and β_{SS2} (testing the difference between set size 4 vs. set sizes 6 and 8). All other factors have two levels and therefore have one contrast coefficient, $\beta_{Factor1}$, which tests the difference between the two factor levels. Consequently, the coefficient estimates cannot be directly mapped to factor levels. For comparisons between the factor levels, we report marginal means estimated from the model.

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[2].

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.

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.

[2] 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 supplementary material.

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

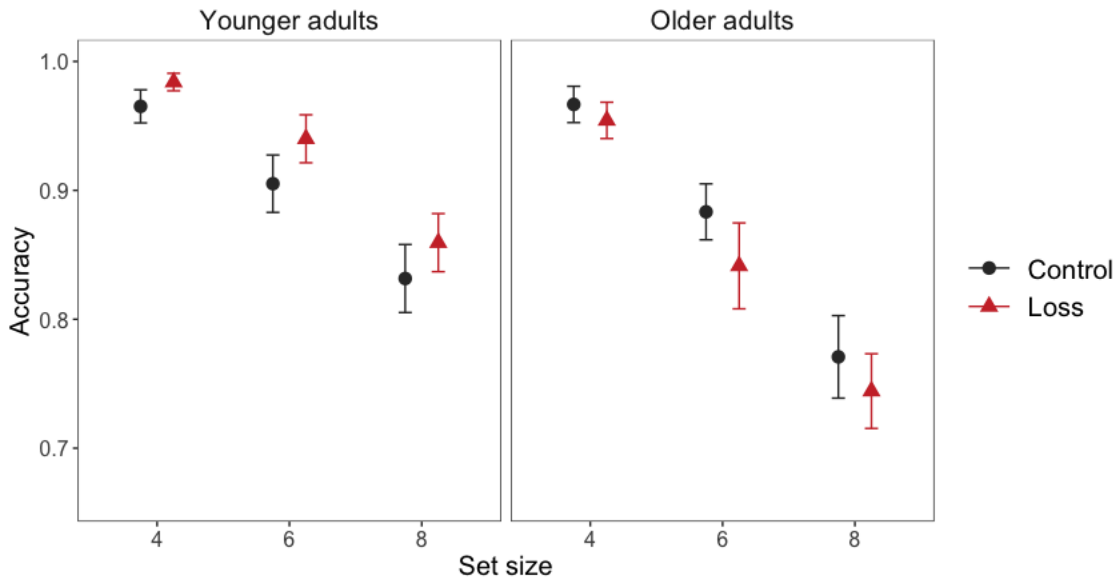
Table 1. Demographics and self-reported Poor Attentional Control (PAC)

		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

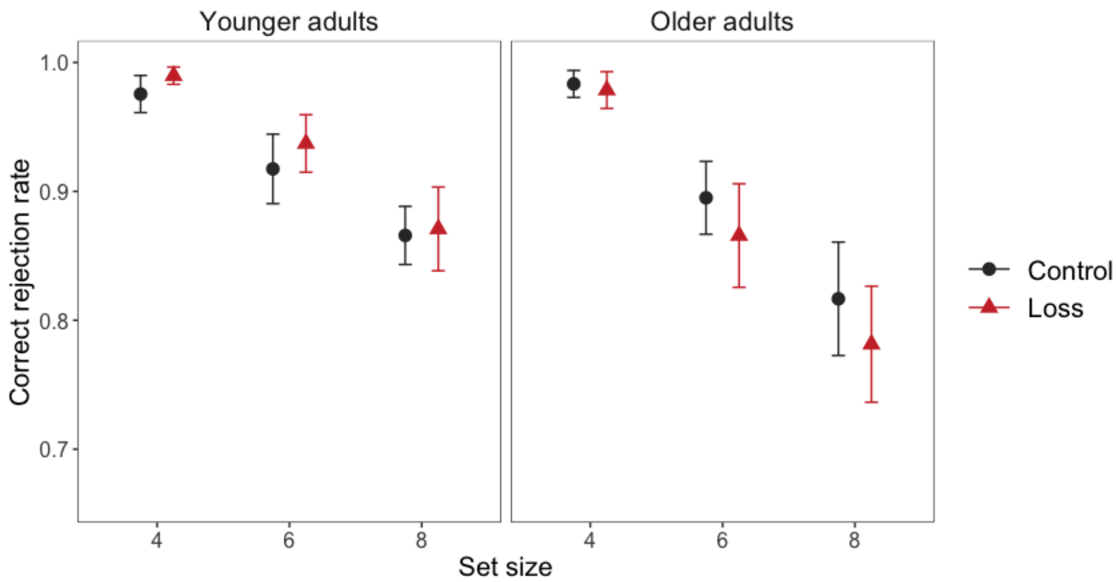
f, female; ERVT, The Extended Range Vocabulary Test; PAC, the Poor Attentional Control scale; MMSE, Mini-Mental State Examination

Behavioral results

All (Accuracy)



New item (Correct rejection)



Old item (Hit)

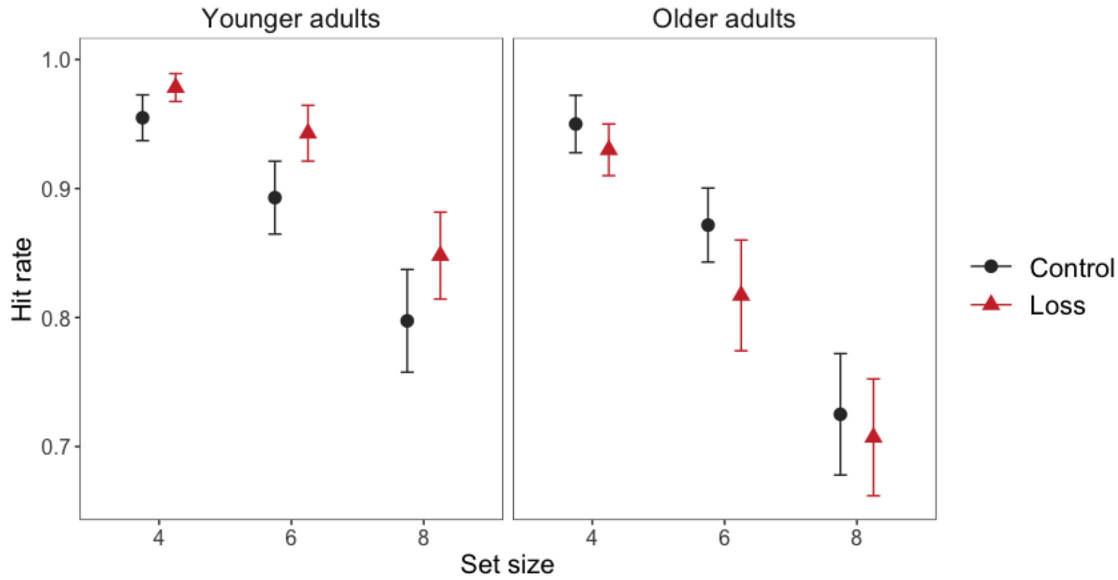


Figure 1. Accuracy data

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 2. Reaction time data (in sec)

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 1) replicated typical effects of age and set size: Young adults outperformed older adults (β_{Age1} = -0.426 [-0.579 -0.275]; marginal model estimate 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])[3]. 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 greater 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.

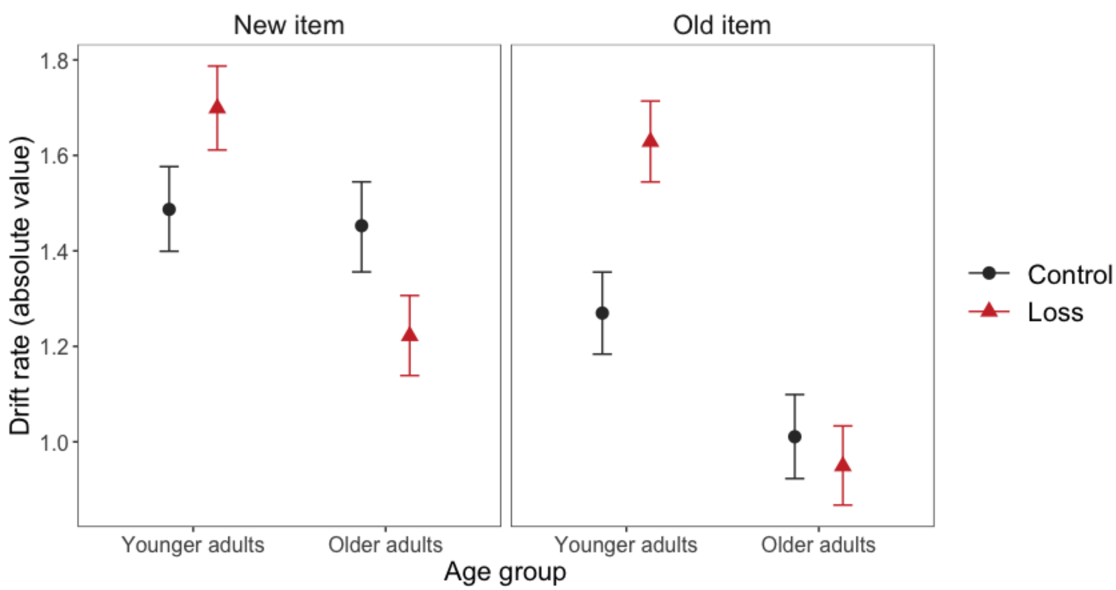
[3] As described in the Methods, β_{SS1} tests the difference between set size 6 vs. set size 8 and β_{SS2} tests the difference between set size 4 vs. set sizes 6 and 8.

For the reaction time data (Table 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).

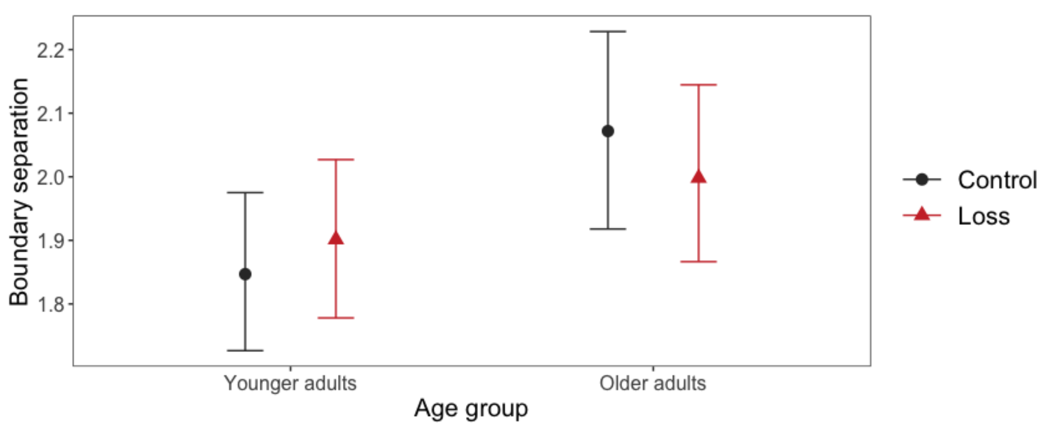
In short, the basic behavioral data suggest that incentive had opposite effects on accuracy for younger and older adults, and no significant effects on response time. The patterns were consistent when we analyzed the effects separately for new and old item trials (middle and bottom panels in Figure 1; 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.

Diffusion model results

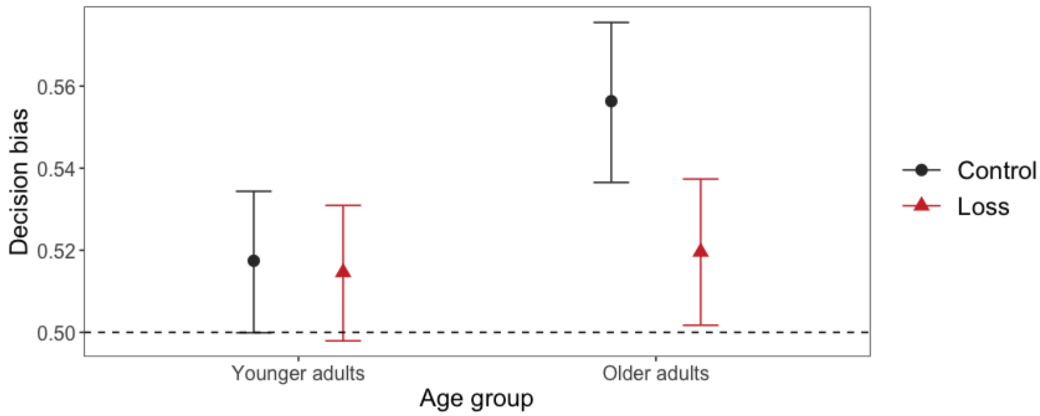
(a) Drift rate



(b) Boundary separation



(c) Decision bias



(d) Non-decision time

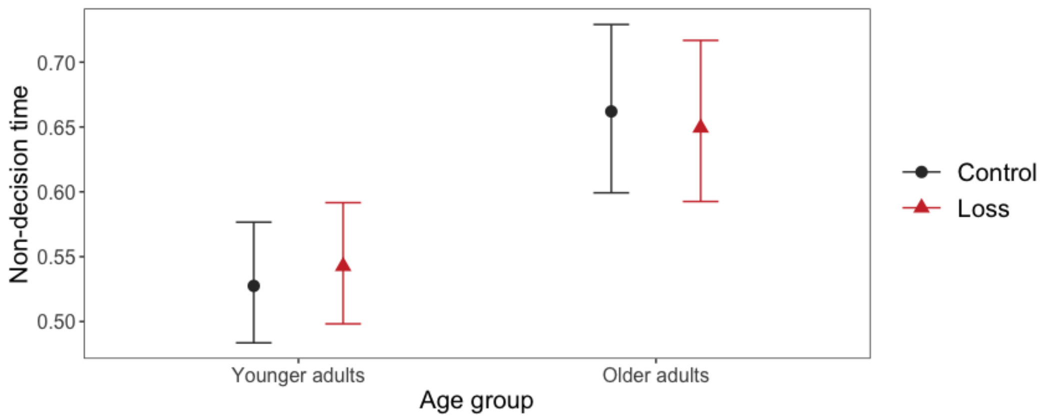


Figure 2. Diffusion model parameters

(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 2a). 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 2a). 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 Materials (S4 for the contrasts; 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 2b). 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 2c). 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 2c, 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 2d). We replicated standard effects of longer non-decision times for older adults (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 Supplementary Material S5 and S12).

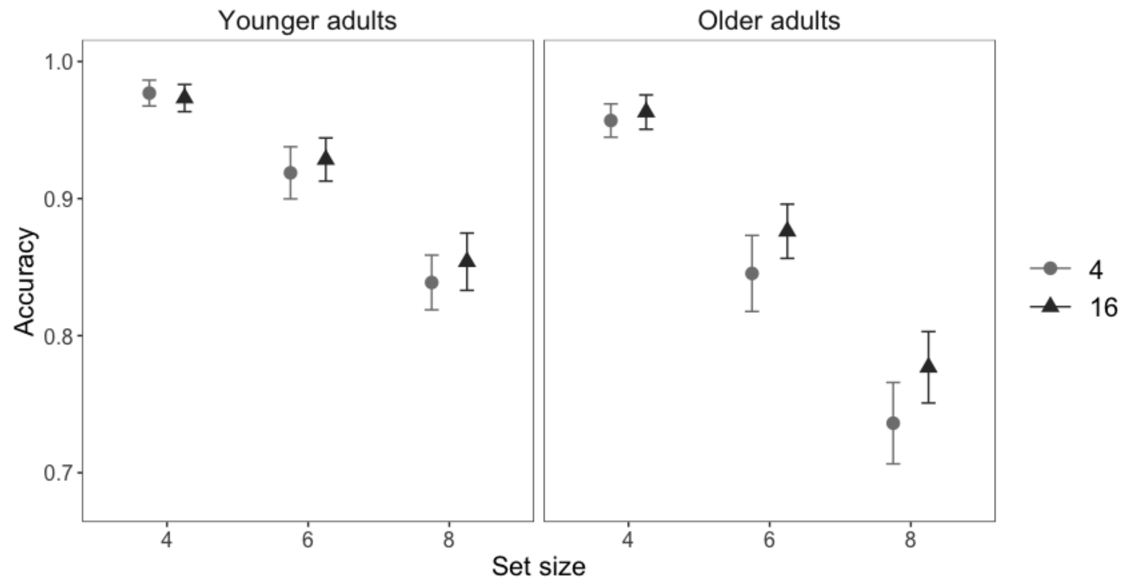
There was an age × incentive interaction on two subscales less related to perceived demand, the self-reported performance subscale ($\beta_{\text{Age1} \times \text{Incentive1}}$ = -5.892 [-11.589 -0.188]) and the newly-added motivation subscale ($\beta_{\text{Age1} \times \text{Incentive1}}$ = -9.419 [-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.

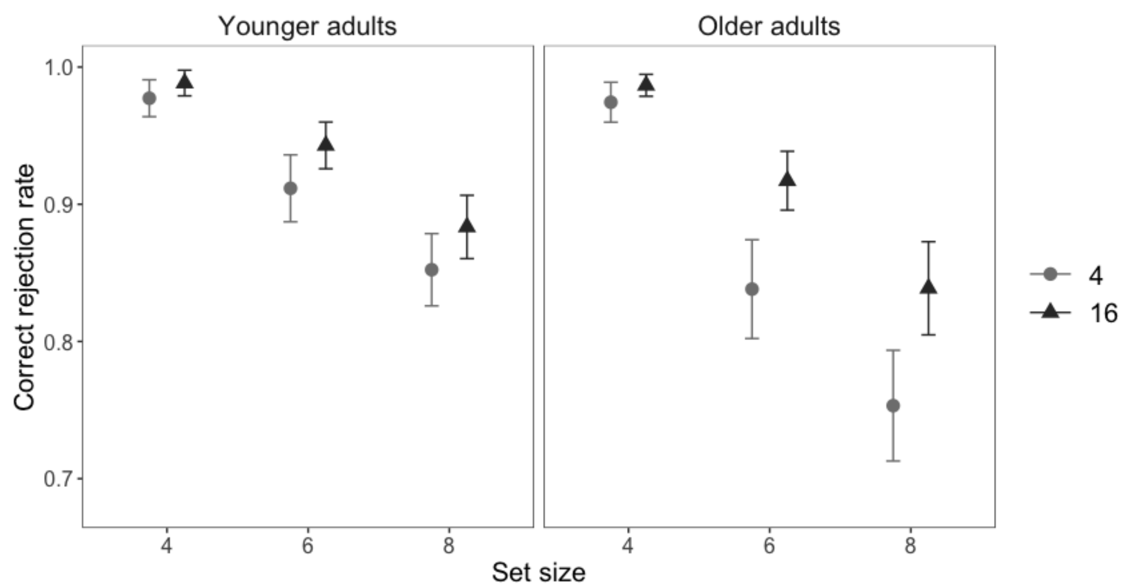
The age × incentive interaction on the motivation subscale suggested that loss incentive increased motivation for younger adults (control = 65.487 [60.326 70.553], loss = 76.694 [71.814 81.634]), but decreased motivation for older adults (control = 84.049 [78.016 89.984], loss = 76.026 [70.166 81.889]). 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

All (Accuracy)



New item (Correct rejection)



Old item (Hit)

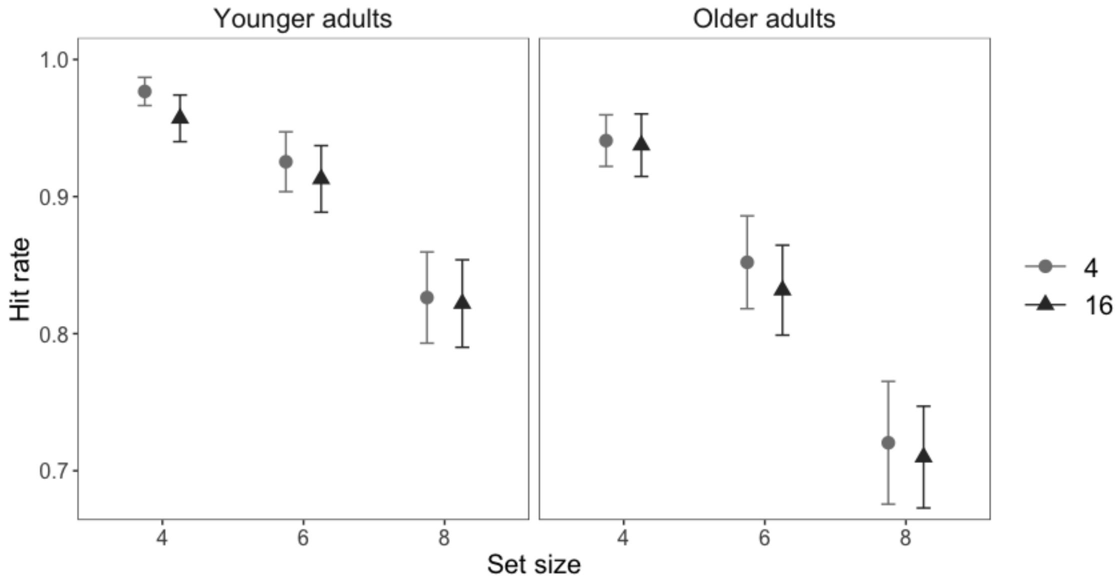


Figure 3. Accuracy data (Retention interval)

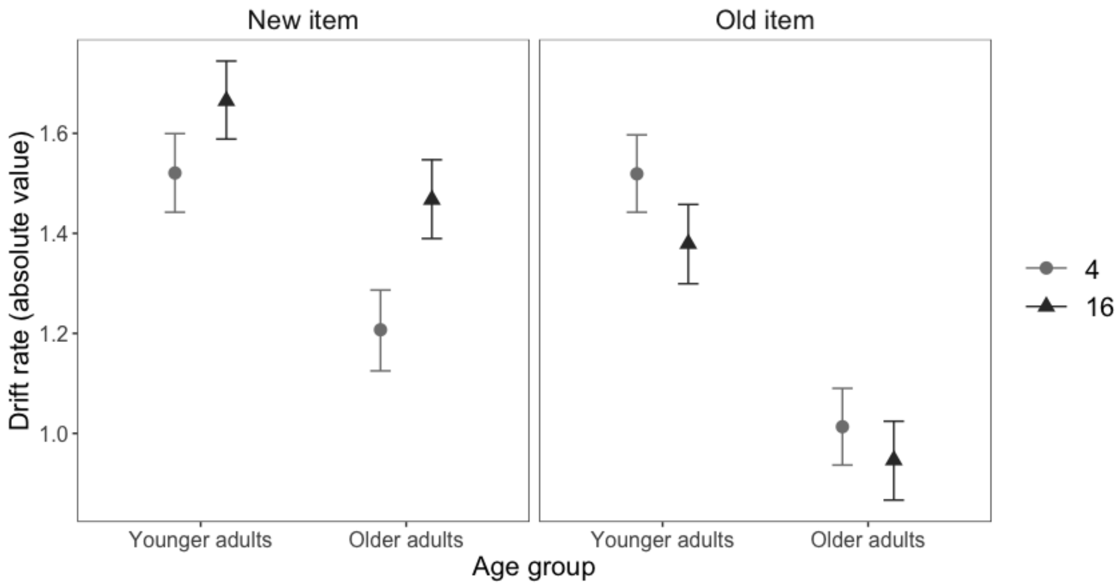
Top panels show accuracy for all trials. Middle and bottom panels show accuracy for new and old item trials, respectively. Shorter retention interval (4 s): gray circle, Longer retention interval (16 s): black triangle. Error bars show 95% confidence interval of the data.

Table 3. Reaction time data (Retention interval)

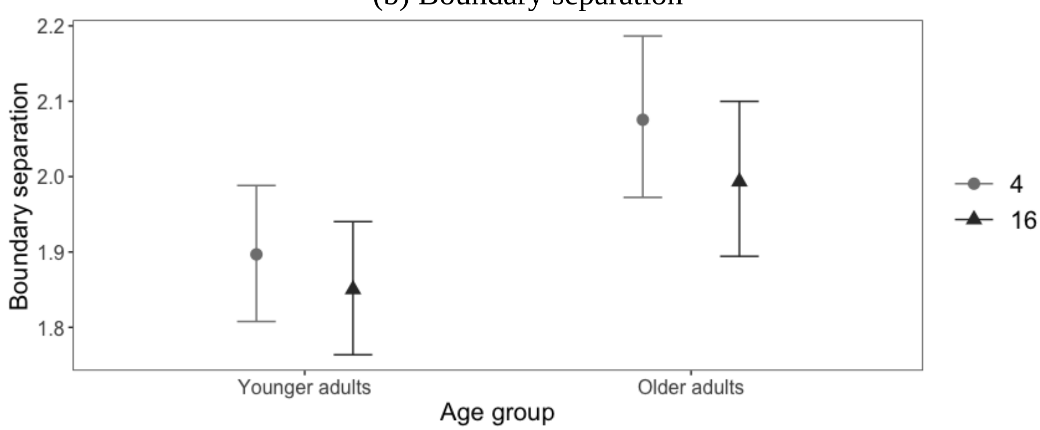
Age	RI	Set size	All items	New items	Old items
YA	Short (4 s)	4	0.994 [0.950 1.038]	0.988 [0.939 1.037]	0.999 [0.954 1.043]
		6	1.121 [1.068 1.174]	1.187 [1.122 1.252]	1.061 [1.010 1.113]
		8	1.167 [1.109 1.225]	1.219 [1.158 1.279]	1.118 [1.055 1.182]
YA	Long (16 s)	4	1.017 [0.966 1.068]	1.020 [0.963 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.

(a) Drift rate



(b) Boundary separation



(c) Bias

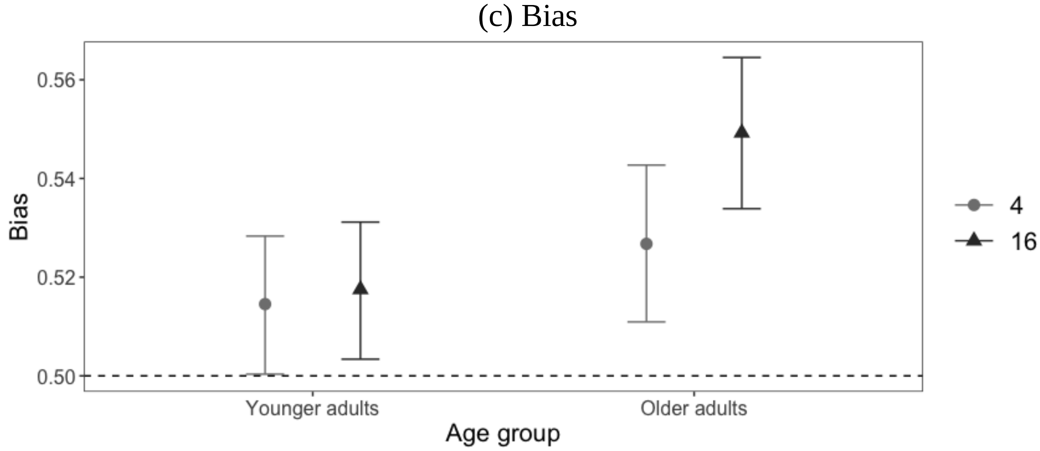


Figure 4. Diffusion model parameters as a function of retention interval. (a) Drift rate. Absolute values are shown for the ease of comparison. (b) Boundary separation. (c) Decision bias. Dashed line (0.5) means no bias. Shorter retention interval (4 s): gray circle, Longer retention interval (16 s): black triangle. 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 greater accuracy (β_{RI1} = 0.099 [0.007 0.188]) and shorter RTs (β_{RI1} = -0.034 [-0.042 -0.025]) (Figure 3 and Table 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 did not approach significance 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. But 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 and Table 3; Supplementary Material S1-S2 and S6-S7 provide full model results and marginal means).

The diffusion model analyses (Figure 4; Supplementary 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 ($\beta_{\text{ProbeType1} \times \text{Age1} \times \text{RI1}}$ = 0.067 [0.004 0.131]; Figure5a).

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 4b). This does not appear to not 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 4c), the age × retention interval interaction did not reach statistical significance ($\beta_{\text{Age1} \times \text{RI1}}$ = 0.039 [-0.003 0.083]).

We include these results for completeness and their potential 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 (Supplementary figure 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; Kimberly Sarah 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 controlled, effortful process. Older adults are not 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).

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. Others 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.

Barouillet 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, and translating that understanding to benefit the real-world performance of both young and older adults.

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