Cognitive flexibility improves memory for delayed intentions

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Abstract

Cognitive control involves the allocation of cognitive resources in order to successfully navigate and interact with the world. Oftentimes, control involves balancing the demands brought on by performing immediately relevant tasks and those required in order to perform future intended actions. For example, directing attention towards navigating through traffic on a highway while also needing to remember to exit the freeway at a particular street. This ability to delay execution of a goal until the appropriate time in the future is referred to as prospective memory (PM). The dual mechanisms of cognitive control (DMC) framework posits that individuals can use two different strategies to remember an intended action: a proactive control strategy involving working memory maintenance of the goal and monitoring of the environment, or a reactive control strategy relying on timely retrieval of goal information from episodic memory. Previous research on prospective memory has demonstrated that performance improves when individuals engage these control strategies in accordance with the demands of the task environment. However, it is unclear how people select a control strategy, particularly in situations with dynamic task demands. We hypothesized that if people flexibly adapt their strategy in response to changes in the environment, this should facilitate prospective memory. Across two experiments, we asked participants to identify the reappearance of a picture target (a prospective memory intention) while at the same time performing an ongoing visual search task. The attentional demands of the ongoing task were manipulated to monotonically increase or decrease on a moment to moment basis. The selection of control strategies was identified using reaction time costs and neural measures of intention maintenance.

Results showed that people fluidly modified control strategies, shifting towards proactive control when the attentional demands decreased, and shifting towards reactive control when attentional demands increased. Critically, these adaptive shifts in control strategy were associated with better prospective memory performance. These results demonstrate that fine-grained control of attention and memory resources serves an adaptive role for remembering to carry out future plans.

1 Introduction

2 Life is busy and keeping track of what we are doing and what we intend to do can
3 be challenging. Cognitive control describes the set of processes by which we are able to
4 maintain and connect goals to actions and to subsequently filter out irrelevant
5 distractors in accordance with these goals¹. Juggling goals in spite of interruptions is a
6 ubiquitous part of everyday life², constituting upwards of 50-80% of our daily memory
7 problems^{3,4}. The cognitive ability to delay the execution of a goal until a precise moment
8 is known as prospective memory (PM). For example, remembering to pick up groceries
9 on your way home from work later today requires PM. How do you accomplish this? The
10 multiprocess theory of PM, which is a specific PM-focused implementation of the more
11 general dual methods of cognitive control framework (DMC⁵⁻⁷), describes two
12 dissociable strategies: *proactive control* and *reactive control*^{8,9}. Proactive control relies
13 on working memory to remember the goal and external attention to monitor the
14 environment for cues to act⁹⁻¹². Reactive control relies on episodic memory to store the
15 goal and salient cues from the environment to trigger its timely retrieval¹³⁻¹⁵.

16 These strategies have been shown to have distinct behavioral and neural
17 profiles. Proactive control is cognitively demanding^{6,16} and interferes with ongoing
18 processing^{10,17}, whereas reactive control relies less on working memory processing and
19 can succeed without any observable interference costs¹⁸⁻²³. Further evidence for this
20 dissociation comes, in part, from observations of individual and age-related differences
21 in PM strategy capabilities. Individual differences in working memory have been more
22 strongly linked to proactive than reactive performance²⁴⁻²⁷. Additionally, age-related
23 impairments in PM, rooted in declining cognitive control capabilities, have been linked to

proactive control deficits^{28–33}, but not to deficits in reactive control^{34,35}. Dissociable neural correlates have also been identified for these strategies^{36–40}. In summary, proactive PM performance is primarily related to sustained activity in anterior prefrontal cortex, as well as other regions of the frontoparietal control network⁴¹, and to working memory maintenance in inferior temporal regions³⁷. The engagement of reactive control mechanisms in response to PM events have been linked to increased connectivity to³⁹ and transient responses in the middle temporal gyrus³⁸, as well as transient responses in the precuneus, ventral parietal cortex, and precuneus^{36,41}.

The DMC posits that successful cognition depends on optimizing the use of proactive and reactive control in response to environmental demands. Preparatory processes involved in proactive control, like strategic monitoring of the environment for intention-relevant cues, may benefit PM, but also place high costs on working memory and attentional capacities. In low-demand environments, controlled attentional processes can be successfully allocated to maintain goal information in working memory and to strategically monitor the environment for the right time and place to act^{6,42,43}. Therefore, in situations of low working memory load or a high probability of a PM event, proactive control should be beneficial. However, when working memory load is high, it is more efficient to offload the PM intention to the reactive control system and redirect cognitive resources towards more immediate demands⁵. For example, when concurrent cognitive demands are high – as one might experience as traffic congestion increases on the commute home – offloading an important PM intention to reactive control (e.g., remembering to stop at the grocery store to buy orange juice) frees resources for other urgent demands (safely navigating the heavy traffic). While reactive

control is less cognitively demanding, it is more susceptible to proactive interference and more vulnerable to lapses in attention to goal-relevant events in the environment^{6,44} (e.g., failing to notice the turnoff for the grocery store and proceeding home sans orange juice). It is therefore important to select a control strategy best suited to the current situation in order to reduce the risk that prospective intentions interfere with more urgent demands, and also to reduce the risk that those intentions go unfulfilled.

One major area of research in PM has been to explain how individuals choose and change strategies in response to variable environmental demands⁴⁵. Gynn^{11,46} proposed that PM performance is in part supported by two dissociable components of proactive control: an all-or-nothing sustained prospective intention component and a more flexible prospective monitoring component. The prospective intention component is described as load-invariant and relative inflexible, while the monitoring component is thought to be dynamically sensitive to environmental factors⁴⁷. Recent related work has suggested that the sustained intention component of this model is also able to be strategically adjusted to some extent^{16,48}, and that the amount of cognitive resources needed to maintain the intention-state can negatively affect monitoring ability⁴⁹. This *monitoring plus intention-state* theory of PM doesn't explicitly account for reactive control, but it acknowledges that there are certainly times when spontaneous retrieval (i.e. reactive control) may be accounting for PM performance.

Many models of PM have focused on the relationship between proactive and reactive control. Some models propose a central executive process that allocates resources either towards proactive or reactive control along a continuum⁵⁰, or strikes some balance between attention to external stimuli (ongoing demands) or internal

stimuli (PM intention maintenance)⁴¹. A recent update of dual-process PM theory, the dynamic multiprocess framework (DMPV^{51,52}), proposes that people have a flexible choice between proactive control and reactive control that primarily depends on the contextual likelihood of a PM event. According to this model, individuals will rely on reactive control when the probability of a PM event is low, but then temporarily “switch on” proactive control when a cue in the environment signals an increased likelihood of the PM event (in support of this theory see^{53–55}). While DMPV hypothesizes a fluid relationship between proactive and reactive control modes, this relationship has yet to be demonstrated. To date, empirical work has only shown that people can perform a bimodal switch between the two strategies following abrupt changes in the environment. In real-world settings, however, the task environment (e.g., the ongoing demands on our cognitive resources) may not always change so abruptly, but rather may fluctuate more gradually from moment to moment. It is unclear how people adjust their PM strategy when situational demands change dynamically over time. For example, remembering to exit the highway at the correct street for the grocery store on the way home while dealing with the ebbs and flows of traffic congestion.

Across two experiments, we evaluated how individuals adjusted their PM control strategies when cognitive demands increased or decreased over time and in turn how this impacted prospective remembering. We hypothesized that adapting one’s control strategy to better align with the cognitive load caused by competing demands (e.g., using a more proactive strategy when attentional resources become available to do so, and using a more reactive strategy when fewer attentional resources are available) should improve prospective remembering. We modified our existing PM paradigm

(Lewis-Peacock et al., 2016³⁷) and required participants to make a delayed target detection with pictures of faces and scenes while also performing an ongoing visual-search task with oriented arrows. The paradigm was modified so that the cognitive demands within a trial could be parametrically varied to create some situations that favor a more proactive control strategy for remembering the target picture (decreasing ongoing demands), and other situations that favor a more reactive control strategy (increasing ongoing demands). The cognitive demands of this task were manipulated by subtly, but monotonically, adjusting task difficulty within each trial. For information on the pilot studies used to validate the task design, see supplementary materials.

We collected two measures of PM strategy use on every trial – a behavioral index (RTs on the ongoing task) and a neural metric (fMRI pattern classification of the PM intention). Our previous work³⁷ suggests that these two measures of PM strategy provide unique and complementary assessments of memory performance in situations with stable cognitive demands, and we anticipated they would also be informative in situations with less stable demands. The RT measure is a behavioral hallmark of proactive control as it reflects dual-task interference costs (“PM costs”) arising from the active maintenance and monitoring of a PM intention^{8,10,56}. The neural measure, derived from multivariate classifier analysis of fMRI data, has been associated with the working memory maintenance of PM intentions^{37,57–59}. In a first experiment, we linked time-sensitive behavioral measures of *changes in PM strategy* within a trial to memory performance (n = 50). We then replicated this experiment while also collecting fMRI data (n = 28). This allowed us to combine neural measures of PM intention processing with behavioral measures of shifts in PM strategy. Performance was similar across both

Experiments 1 and 2, therefore all behavioral data were pooled for subsequent analyses (see supplementary materials for separated analyses of behavioral and fMRI samples). To evaluate the consequences of cognitive flexibility in dynamic environments, we linked these behavioral and neural measures of PM strategy to PM accuracy on a trial-by-trial basis.

Results

Task Overview

The dual-task paradigm used here to evaluate PM strategy selection and modification was adapted from the design of Lewis-Peacock et al. (2016)³⁷. Participants solved a delayed target recognition task for a picture of a face or a scene (the PM task) while concurrently performing a visual search task every 2s on an array of tilted arrows (the ongoing task; **Figure 1**, see supplementary materials for more details on task design). The ongoing task required participants to indicate whether a rightward facing horizontal arrow was present or absent in a circular array of arrows. Ongoing task (OG) difficulty was manipulated by adjusting the degree to which the angles of distractors were similar to the horizontal plane. Difficulty could increase or decrease across a trial, or remain fixed at the middle difficulty level (difficulty level 8 out of 15). For increasing and decreasing trials, difficulty shifted monotonically at the rate of one difficulty level every 2s (i.e. shifted on each new probe display). Trials began with the presentation of the trial-unique PM target, followed by 1 to 15 probe displays. On each probe display, participants could respond either “present” or “absent” to the ongoing task, or “target” to the PM task, but not both. PM targets appeared on the last probe of each trial, and were followed by PM-task feedback (2s), and then by a break (6s) before the next trial.

Figure 1. Task design. *Left:* Ongoing task difficulty could increase or decrease every 2s across a trial or remain fixed at the middle difficulty level (8 of 15). *Right:* In the dual-task PM experiment, participants identified the reappearance of a PM target while concurrently performing the ongoing task.

Ongoing Task Performance

Participants performed well on the ongoing (OG) task (mean accuracy = 83.64%, 95% CI = [75.49%, 91.79%]) as summarized in **Figure 2**. There was no interaction between trial type (PM trials versus non-PM trials) and task difficulty ($\beta_{\text{interaction}} = 6.2 \times 10^{-4}$, 95% CI = [-0.001, 0.002], $p_{\text{interaction}} = 0.468$) on OG task accuracy. OG accuracy decreased as difficulty increased, and there was a small, but reliable main effect of trial type between PM and non-PM trials ($\beta_{\text{diff}} = -.026$, 95% CI = [-0.027, -0.025], $p_{\text{diff}} < .001$; $\beta_{\text{pm}} = 0.008$, 95% CI = [0.001, 0.016], $p_{\text{pm}} = 0.024$; marginal $r^2 = 0.57$; **Figure 1A**). The main effect of trial type indicated a dip in OG accuracy of less than 1% on PM trials compared to non-PM trial. A follow-up analysis compared OG accuracies from PM and non-PM trials at each difficulty level, finding that accuracies were only reliably different at difficulty level 8 on fixed difficulty trials ($p = 0.025$, after Bonferroni correction factor 15). On dynamic trials (increasing and decreasing difficulty), the main effect of PM task on OG accuracy was not significant ($\beta_{\text{pm}} = 0.007$, 95% CI = [-8.5 $\times 10^{-5}$, 0.015], $p_{\text{pm}} = 0.052$). We also found that at the hardest difficulty level of the OG task (15), participants

were still performing well above chance (mean = 61.43, $t(77) = 80.39$, $p < .001$, 95% CI = [59.90%, 62.95%]).

Measuring the difference in RTs on an ongoing task between PM and non-PM trials is one of the primary methods for inferring PM strategy use⁸. A large difference in OG RTs between PM and non-PM trials implies the use of proactive control on the PM trials, whereas a small difference implies the use of reactive control on the PM trials. Here, we found an interaction in OG RTs between condition (PM and non-PM trials) and difficulty level (1 to 15) ($\beta_{\text{interaction}} = 0.011$, $p < .001$, 95% CI = [0.010, 0.013]; **Figure 2B**). At the hardest difficulty level, RTs were well below the response deadline of 1900ms ($t(77) = 38.401$, $p < .001$, mean RT = 1264ms, 95% CI = [977ms, 1551ms]), demonstrating that participants were performing above floor. The difference in OG RT between PM and non-PM trials (referred to as “PM cost” from here on out) was then calculated for each participant at each difficulty level. These data were replotted in this fashion, and they reveal that average PM costs varied systematically as a function of OG task difficulty ($\beta_{\text{cost}} = -10.35$, $p < .001$, 95% CI = [-12.29, -8.42]; **Figure 2C**). This suggests that PM strategy shifted flexibly between proactive control and reactive control as the OG task increased in difficulty, and vice versa.

Figure 2. Behavioral performance. a) Ongoing task accuracy across difficulties, error ribbons $\pm$ 1 SEM. PM: dual-task trials with a PM intention; Non-PM: ongoing task only without a PM intention. b) Ongoing task RT (correct responses only) across difficulties, error ribbons $\pm$ 1 SEM. c) PM cost (the difference between ongoing task RT for PM trials vs. Non-PM trials) was computed for each participant at every difficulty level. Violin plots represent the distribution of by-participant average costs at each difficulty. PM cost is highest at easy difficulty levels (dark red) and decreases as task difficulty increases (dark blue). d) PM cost slopes were calculated as the change in PM cost within each trial. Violin plots show the average within-trial PM cost slopes for decreasing (Dec), fixed (Fix), and increasing (Inc) trials across participants. * $p < .05$. e) PM accuracy for each participant across trial types. f) Logistic regression bootstrap analysis linking PM cost slope to PM accuracy for decreasing (red) and increasing (blue) trials. Each individual red/blue line shows the predicted relationship for each bootstrapped sample ($n=10,000$). White lines reflect the fixed-effects relationship for the original sample. * $p < .05$.

To evaluate whether this linear shift in PM strategy across task difficulty levels held within individual trials, we computed 1st, 2nd, and 3rd order polynomial regressions between PM cost and OG difficulty separately for each trial. If PM strategy selection

was bimodal (i.e., an all-or-none “flip” between proactive and reactive control), then individual trials should be best fit by a 3rd order polynomial. However, if the relationship was more fluid, then a 1st or 2nd order polynomial should fit the data better. Additionally, if the data demonstrate a dramatic U-shaped or asymptotic curve, instead of a linear fit, a 2nd order polynomial should fit better than the 1st order polynomial. We compared Akaike information criterion values (AICc, with a correction for small sample sizes) for each model for correct responses on each trial, and used Akaike weighting to compare relative model fits. We found that a 1st order polynomial (linear model) fit best for nearly all trials (mean = 93.43%, 95% CI = [92.62%, 94.24%]; Akaike weight = 0.873, 95% CI = [0.865, 0.880]), compared to 2nd order fits (mean = 5.72%, 95% CI = [4.99%, 6.45%]; Akaike weight = 0.111, 95% CI = [0.104, 0.119]), or 3rd order fits (mean = 0.85%, 95% CI = [0.68%, 1.02%]; Akaike weight = 0.016, 95% CI = [0.012, 0.019]). This result provides evidence that the engagement of control strategies changed fluidly and linearly with changes in OG task demands within a PM trial.

Next, we evaluated whether changes in PM cost within a trial were different for increasing-, decreasing-, and fixed-difficulty trials. To do this, we computed a within-trial measure of linear shift in PM cost from the beginning of the trial to the end of the trial, which we shall refer to as *PM cost slope*. We found that PM cost slopes varied systematically across trial types ($F(2,154) = 47.02$, $p < .001$; **Figure 2D**). PM cost slopes were negative on increasing trials (mean = -1.14 ms/s, 95% CI = [-2.24,-0.42], $t(77) = 2.07$, $p = 0.042$), and they were positive on decreasing trials (mean = 6.03ms/s, 95% CI = [5.44, 6.62], $t(77) = 10.23$, $p < .001$) and fixed trials (mean = 3.34ms/s, 95% CI = [2.07, 4.61], $t(77) = 5.24$, $p < .001$). In this task design, a PM target appeared at the

end of every PM trial. Thus, positive PM cost slopes (i.e., a shift towards proactive control) on fixed difficulty trials likely arose from an increase in PM expectancy as each trial progressed^{60,61}. Expectancy should impact all trial types equally, and yet there were meaningful differences between conditions. Planned pairwise comparisons revealed that PM cost slopes increased step-wise from increasing trials to fixed trials ($F(77) = 37.14$, $p < .001$) and from fixed trials to decreasing trials ($F(77) = 15.1$, $p < .001$).

Prospective Memory Task Performance

On average, participants identified the PM target on three-quarters of the trials (mean PM accuracy = 74.57%, 95% CI = [56.82%, 92.31%], with no differences in accuracy across trial types ($F(2,154) = 0.679$, $p = 0.508$; **Figure 1E**). The false alarm rate, defined as PM-target responses on probes where the target was not present, was low (mean = 0.60% of probes, 95% CI = [-0.72%, 1.92%]). Because PM accuracy was stable across the dynamic trial types (increasing and decreasing difficulty trials), and OG accuracy was not impacted by the presence of the PM task on these trials, we concluded that participants were not sacrificing accuracy on one task in order to perform the other. Therefore, any RT differences on the OG task during PM trials could reasonably be interpreted as reflecting differences in strategy used to perform the PM task, rather than a speed/accuracy tradeoff between the dual tasks.

Linking Shifts in PM Strategy to PM Performance

We reasoned that shifts in PM strategy might occur as individuals attempted to preserve performance on the PM task while demands of the OG task shifted over time. To evaluate this idea, we tested the relationship between *PM cost slope* and *PM*

accuracy across all trials. We used bootstrapped logistic regression to relate these two measures separately for increasing and decreasing trials (**Figure 2F**). On decreasing trials, larger *positive* PM cost slopes (reflecting a shift towards proactive control) were related to better PM performance ($\beta_{\text{dec}} = 0.018$, $p < .001$, 95% CI = [0.008, 0.028]). On increasing trials, larger *negative* PM cost slopes (reflecting a shift towards reactive control), were numerically related to better PM performance, but this relationship did not reach statistical significance ($\beta_{\text{inc}} = -0.006$, $p = 0.119$, 95% CI = [-0.015, 0.004]). Critically, there was an interaction of PM cost slope and trial type on PM accuracy, with the direction of PM cost slope leading to different consequences on increasing vs. decreasing trials ($\beta_{\text{interaction}} = 0.024$, $p < .001$, 95% CI = [0.011, 0.037]). On fixed trials (data not shown), the relationship between PM cost slope and PM accuracy was positive ($\beta_{\text{fix}} = 0.020$, $p = 0.003$, 95% CI = [0.006, 0.033]), which was similar to decreasing trials ($\beta_{\text{diff}} = 0.001$, $p = 0.423$, 95% CI = [-0.015, 0.017]) but significantly more positive than on increasing trials ($\beta_{\text{diff}} = 0.025$, $p = 0.001$, 95% CI = [0.009, 0.041]).

The relationship between PM cost slope and PM accuracy survived after controlling for other possible explanatory variables. Partial regression analyses evaluated, one at a time, the impact of *OG accuracy*, *OG RT*, *OG RT slope*, and *average PM cost* on the predictive link between PM cost slope and PM accuracy (see supplementary materials). These control analyses confirmed that PM cost slope explained a significant proportion of variance in PM accuracy, and did so to a greater extent than all other variables.

This same by-trial relationship between PM cost slope and PM accuracy existed across participants as well. Participants who on average showed larger shifts towards

proactive control (more positive PM cost slopes) benefited more on decreasing trials, and participants who showed larger shifts towards reactive control (more negative PM cost slopes) benefited more on increasing trials ($\beta_{\text{interaction}} = -0.018$, $p = 0.002$, 95% CI = $[-.013, -.024]$, data not shown). In summary, these results provide behavioral evidence that individuals shifted PM strategy from moment to moment in response to changing OG task demands. These shifts in cognitive control were adaptive because their direction and magnitude were related to successful PM performance.

Neural Measures of PM Intentions

For the participants who performed this task in the MRI scanner (N=28), we evaluated whether a neural measure of PM intention-related brain activity³⁷ could provide additional insight into the link between PM strategy selection and memory performance. First, we identified regions that were significantly engaged by the PM task above and beyond the OG task in isolation (**Figure 3A**; for more details see methods and supplementary materials). These regions are consistent with previous literature on PM intention maintenance^{36,37,39,41}. From these brain regions, fMRI pattern classifiers were used to quantify the degree of PM intention-related processing across each trial. The strength of PM intention processing was operationalized as the difference in classifier evidence for the PM-relevant category vs. the PM-irrelevant category (e.g., “face – scene” for a face-target PM trial). Trained classifiers (for more details see methods and supplementary materials) performed well above chance at predicting the category of the current trial’s PM target (classifier AUC for faces: 86.94, SE = 0.01; scenes = 88.54, SE = 0.01; non-PM trials: 83.76, SE = 0.01; and rest = 99.62, SE =

4.7*10⁻⁴). Across trials, this neural measure varied systematically with OG task difficulty (Figure 3B). The neural evidence of PM intention processing decreased as task demands increased ($\beta = -0.005$, $p < .001$, 95% CI = [-.008, -.002], marginal $r^2 = .039$).

Figure 3. fMRI decoding of PM intentions. a) Brain regions significantly engaged by the addition of the PM task to the OG task (GLM contrast PM > Non-PM, FDR corrected at $p < .001$). al = anterior insular cortex, dACC = dorsal anterior cingulate cortex, dIPFC = dorsal lateral prefrontal cortex, IPS = Intraparietal sulcus, LOC = lateral occipital cortex, mOCC = medial occipital cortex, rIPFC = rostral lateral prefrontal cortex, VTC = ventral temporal cortex. These regions were used as the initial feature mask to train and test fMRI pattern classifiers for PM intention-related activity. b) PM intention evidence (EV; the difference between classifier evidence for the PM target's category and the non-target category) was computed for each participant at every difficulty level, and group data is shown in violin plots. PM intention evidence was highest at easy difficulties (dark red) and lowest for the most difficult levels (dark blue). c) The relationship between PM intention evidence and PM accuracy was computed using bootstrapped logistic regression ($n=10,000$ iterations) for decreasing (red) and increasing (blue) trials. * $p < .05$.

Within trials, however, the neural measure of PM intention processing did not vary systematically across timepoints (mean slope of PM intention evidence = 0.007 EV/s, 95% CI = [-0.002, 0.016], $t(27) = 1.57$, $p = 0.128$). There were also no differences in by-trial PM intention evidence slopes across increasing, decreasing, and fixed difficulty trials ($F(2,54) = 1.35$, $p = 0.269$). The stable level of PM intention processing over the course of a single trial may be a measurement limitation due to the temporal sluggishness of the BOLD signal. Alternatively, it could also reflect the engagement of a

prospective “retrieval mode”^{11,40,46}, which has been described as a more sustained and relatively inflexible component of proactive control that involves PM-items being held in some prioritized state of working memory⁴⁷. Therefore, we computed the *average* classifier evidence for the PM intention on each trial and related this (rather than the slope) to PM accuracy. A mixed-effect ANOVA confirmed that there were no overall differences in average PM intention evidence across trial types ($F(2, 54) = 0.40$, $p = 0.670$). This result was expected because increasing and decreasing trials spanned the same range of difficulty levels (e.g., 1 to 15 vs. 15 to 1). We found that average PM intention evidence correlated positively with PM accuracy on decreasing trials ($\beta_{\text{dec}} = 0.754$, $p = .017$, 95% CI = [0.047, 1.50]; **Figure 3C red**) and fixed trials ($\beta_{\text{fix}} = 0.976$, $p = .039$, 95% CI = [-0.121, 2.062]; not shown), but not on increasing trials ($\beta_{\text{inc}} = 0.280$, $p = 0.255$, 95% CI = [-0.679, 1.123]; **Figure 3C blue**). There were no reliable differences in this statistic between increasing trials and either decreasing trials ($\beta_{\text{interaction}} = 0.474$, $p = 0.199$, 95% CI = [-0.627, 1.623]) or fixed trials ($\beta_{\text{interaction}} = 0.223$, $p = 0.361$, 95% CI = [-1.119, 1.473]).

Combining Behavioral & Neural Measures to Predict PM Performance

We sought to test whether combining both the time-sensitive but indirect behavioral metric of PM cost slope (putatively reflecting dynamic shifts in PM strategy) and the coarser but more direct neural metric of PM intention evidence (putatively reflecting sustained PM engagement) could improve our prediction of PM accuracy on a trial by trial basis. There was no by-trial correlation between these measures (mean $r = 0.02$, 95% CI = [-0.36, 0.39], $p = 0.92$), suggesting that the two metrics could provide

unique information about task performance. We performed a bootstrap analysis to calculate the Akaike information criterion (AIC) values for models predicting PM accuracy including all possible combinations of the predictors *PM cost slope*, *PM intention evidence*, and *trial type* (increasing/decreasing). We then selected the best performing model that included (1) a neural and a behavioral metric, (2) only a behavioral metric, or (3) only a neural metric. Next, we converted AIC scores for these three models to Akaike weights (wAIC), allowing us to directly compare AIC values as conditional probabilities⁶². The results show that the combined Behavior & Neural model (the full model including all main effects, all two-way interactions, and the three-way interaction of PM cost slope, PM intention state, and trial direction) was the best model (Wilcoxon median Akaike weight = 0.889, Wilcoxon 95% CI = [0.883, 0.896], $p < .001$; **Figure 4A**). This combined model was significantly more likely than either the best Behavior-only model (Wilcoxon median ratio = 149.91, wilcox 95% CI = [135.47, 165.63], $p < .001$) or the best Neural-only model (Wilcoxon median ratio = 4.5×10^9 , Wilcoxon 95% CI = [3.9×10^9 , 5.2×10^9], $p < .001$).

Figure 4. Model comparisons using behavioral and neural metrics to predict PM performance. Model weights and R^2 values were computed across bootstrap iterations

($n = 10,000$) to test model differences. a) Akaike weights ($wAIC$) across bootstrap iterations for each model. b) Explanatory power of each model (R^2) shown as distributions across bootstraps. Medians are indicated by dashed grey lines.

We also found that on average the Behavior & Neural model explained the most variance in PM accuracy, with an R^2 value of approximately double that of the best Behavior-only model ($R^2 = .052$ vs. $.028$, **Figure 4B**). Having found that the full Behavioral & Neural model was the best predictor of PM performance, we further investigated the relationships in the model for reliability using the bootstrap approach. We found that although including the three-way interaction term and multiple two-way interaction terms improved the model fit, the only statistically reliable interaction was that of *PM cost slope* and *trial direction* ($p = 0.026$). Additionally, we found that PM intention evidence reliably had a positive relationship to PM accuracy on decreasing difficulty trials (mean = 0.027 , $p = 0.024$), but that relationship was not reliable on increasing difficulty trials (mean = -0.003 , $p = .395$). In summary, our model tests revealed three main results: 1) Including both the neural and behavioral metrics of proactive control improved prediction of PM accuracy over using either metric independently. 2) PM cost slope was differentially predictive of PM accuracy for increasing vs. decreasing trials, replicating the relationship from our behavior-only analysis above (**Figure 2F**). 3) Higher levels of PM intention evidence were positively related to PM performance on decreasing difficulty trials, but there was no reliable relationship on increasing difficulty trials. See the supplementary material for further information on the model fit analyses.

Discussion

This study investigated how navigating an environment with rapidly shifting cognitive demands impacts how we remember to perform future actions. A delayed-recognition prospective memory (PM) task was combined with a dynamic visual search ongoing (OG) task that varied in difficulty from moment to moment. When task difficulty was low, there was greater behavioral interference from the PM task (“PM cost”: slower RTs in the OG task) and stronger neural representation of the PM intention (“PM intention evidence”: classifier evidence for the PM target category in PM-sensitive brain regions). Both of these measures reflect components of proactive control⁵, and they were negatively correlated with OG task difficulty. The behavioral measure varied from moment to moment within a trial according to the task demands, whereas the neural measurement was stable within a given trial but varied across trials. Combining these behavioral and neural measures provided the best prediction of PM accuracy from trial to trial. Together, these results suggest that individuals dynamically adjusted their PM strategy in response to changes in environmental demands. Critically, we found that these shifts in PM strategy were adaptive because greater shifts (in the appropriate direction towards proactive or reactive control) were related to improvements in PM performance. The present results demonstrate that the ability to flexibly adjust cognitive control strategies, in response to changes in environmental demands, is an important contributor to successful execution of delayed intentions.

Our results are consistent with the dual mechanisms of cognitive control framework^{5,6} and the dynamic multiprocess framework of PM^{51,52}. Both dual-mechanism frameworks posit that individuals can use two different methods of cognitive control to fulfill prospective intentions, and that they can flexibly adjust their control strategy in

response to environmental factors, such as cognitive load or PM target expectancy. However, neither framework formally describes whether that adjustment is a fluid process or all-or-none “switch” between strategies. Here, our evidence suggests that there are graded levels of control between proactive and reactive control that people engage along a continuum.

We computed two distinct metrics of proactive strategy use: a time-sensitive behavioral measure of PM cost, and a more tonic neural measure of PM intention processing. The amount of PM costs (the behavioral measure) has been repeatedly linked to levels of strategic monitoring for the PM intention^{8,10}. Here, we found that *changes* in the amount of PM costs over the course of a trial were associated with better performance (**Figure 2F**). The DMC framework suggests that proactive control would be favored on decreasing difficulty trials, when the OG task becomes progressively easier, because attention and working memory resources should be readily available to accomplish both the OG task and PM task successfully. On these trials, the benefit of strategically monitoring for the PM intention may be worth the extra cost incurred in RTs on the OG task. Our results support this idea, showing that when participants reallocated cognitive resources to use proactive control on the PM task (positive PM cost slopes within a trial), PM performance improved.

Conversely, on increasing difficulty trials, when the OG task becomes progressively more difficult, the DMC framework predicts that reactive control would be favored. When there are not sufficient resources to allocate to both the PM task and the OG task, the ability to strategically monitor for the PM intention is compromised, and reliance on this process may lead to deficits in PM performance. Such deficits may arise

from interference in working memory caused by failed attempts to maintain a robust representation of the PM target in the face of distractors, a reduced ability to shift attention between the two tasks in order to strategically monitor for the PM cue effectively, or a reduced ability to perform the PM intention even after noticing a prospective cue^{49,63,64}. Consistent with these ideas, we found that when participants did not divert cognitive resources away from the PM task as OG task difficulty increased (i.e., when PM cost slopes were *positive* on these trials), PM performance suffered.

 Guynn’s two-component model of proactive control^{11,46}, dissociates a flexible, strategic monitoring component from a more tonic component referred to as the “PM-retrieval mode”, which involves sustained maintenance of the PM task set. In the present study, we believe that the behavioral measure of PM cost likely reflects the strategic monitoring component of this model, whereas the neural measure of PM intention evidence likely reflects the PM-retrieval mode. Our results implicated neural regions associated with working memory^{57–59}, including the anterior prefrontal cortex, with this neural measure. However, we found that regions known to support perception and working memory for the specific PM intentions used here (i.e., the ventral temporal cortex^{65,66} for face and scene stimuli) were most important for identifying PM intention maintenance (as identified by a surface-based searchlight analysis^{67,68}; see the supplementary materials). We found that on decreasing difficulty trials (which, according to the behavioral analysis, favor a shift towards proactive control), PM intention maintenance was positively correlated with memory performance, but on increasing trials (which favor a shift towards reactive control) it was not (**Figure 3C**). Although individuals sometimes exhibited a high level of PM readiness, this did not influence task

performance in situations that favored reactive control. These results are in line with previous research suggesting that PM intention maintenance could be beneficial to PM performance in some situations, but was not *necessary* for successful realization of PM intentions in all situations⁴⁰.

The DMPV framework^{51,52} also posits that in contexts where PM occurrence is highly probable, individuals are biased towards and benefit from using proactive control. In our study, participants knew that a PM target would reappear relatively soon after it was introduced (between 2-30s later). On trials with fixed difficulty, we found a consistent increase in PM costs across each trial (positive PM cost slopes), and greater increases in cost were related to better PM performance. This indicates a beneficial, perhaps default, shift towards proactive control in this paradigm for which there is an increasing probability of a PM event throughout each trial. Shifts towards proactive control were even stronger (and beneficial for performance) on decreasing difficulty trials as more cognitive resources became available over time. In contrast, participants shifted away from proactive control on increasing difficulty trials, as cognitive resources were being consumed more and more by ongoing demands over time.

An alternative explanation for the present results is that shifts in PM cost may not reflect shifts between proactive and reactive control strategies per se, but rather shifts between stronger and weaker levels of proactive control. Unitary models of PM such as the preparatory attention and memory “PAM” theory¹⁰ propose that successfully fulfilling prospective intentions relies on some level of proactive preparation in all situations. However, we believe this interpretation of our data is less likely than the dual-mechanisms account. According to the PAM model, we should expect extremely poor

PM performance when evidence of proactive control is absent, and this was not the case. On trials when the PM target appeared while PM costs were high, detection accuracy of the PM target was quite good (mean = 76.62%, SEM = 1.94%; average N = 37.7 trials/participant). However, on trials where PM costs were absent (indicating no evidence of proactive control) when the PM target appeared, accuracy was worse ($t(76) = 4.684$, $p < .001$), but still relatively good and well above floor (mean = 67.81%, SEM = 2.67%, N = 12.1 trials/participant). PM performance was also strong on trials where the neural measure of PM intention evidence was absent (mean = 81.1%, SE = 3.2%, average N = 11.5 trials/participant), and also on trials where both PM cost and PM intention evidence were absent (mean = 70.5%, SE = 6.5%, average N = 2.8 trials/participant). Incidentally, the link between PM cost and PM accuracy in the present study closely replicates prior work from our lab³⁷ where PM accuracy was 66.0% (SEM: 4.1%) when participants were biased towards reactive control, and 71.2% (SEM: 3.0%) when participants were biased towards proactive control.

One limitation of the current study is its reliance on the behavioral PM cost measure to infer PM strategy use. While this has become a standard approach, PM cost is nonetheless an indirect measure of PM strategy, the underlying source of which is still under debate^{53,69–71}. We sought to complement this indirect measure with a more direct measure of PM intention processing using fMRI pattern classifiers to track PM intention maintenance. However, fMRI is sluggish and not ideal to observe time-sensitive shifts in neural coding. It is possible that our neural measure incorporates aspects of both PM-intention maintenance as well as strategic monitoring. However, these neural measures were not correlated with PM cost slopes, which are believed to reflect changes in

monitoring. In addition, previous work has found that in contexts where participants are biased towards reactive control, the level of monitoring is not related to PM performance^{18,72}, however it is related to PM performance when participants are biased towards proactive control^{37,53,72}.

We find that our behavioral and neural metrics provide complementary but independent information about PM performance, approximately doubling our model's predictive power when the neural measure of PM intention maintenance was combined with the behavioral metric of PM cost slope (**Figure 4B**). This result suggests that our measures are capturing different components of proactive control, though the current design does not specify the relative contribution of strategic monitoring versus PM intention maintenance. A future direction will be to use a more time-sensitive neural measure like EEG (electroencephalogram) and eye-tracking to measure active maintenance of PM intentions in dynamic environments, as well as to better identify late-retrieval mechanisms that are characteristic of reactive control strategy use.

In conclusion, here we developed a novel dual-task paradigm to show that people solve prospective memory problems by flexibly shifting between proactive control and reactive control in response to changes in ongoing cognitive demands. We found evidence for two different components of proactive control – strategic monitoring, measured behaviorally, and PM intention maintenance, measured neurally – which independently fluctuate and contribute to PM performance. These shifts were adaptive in that adjustments of control towards the strategy favored for a given situation (e.g., shifting towards proactive control when demands decreased across time) led to better PM performance. These results extend dual mechanism accounts of PM by

demonstrating that cognitive flexibility (i.e., adapting cognitive control strategies to the environment) is beneficial for remembering to perform future intentions.

Methods

In this experiment we had 78 healthy young adult participants (28 neural sample, 17 F, mean age = 21.8; 50 behavioral sample, 31 F, mean age = 19.2), perform an ongoing visual search task with an embedded PM task (**Figure 1**). The ongoing task here was a visual-search task (“OG task”) where participants searched for a specific target arrow on a circular array of oriented arrows (**Figure 1A**). We chose this as the OG task due to the ability to systematically and parametrically manipulate task difficulty by adjusting distractor parameters along a continuum⁷³. The ongoing task target arrow was always a rightward facing horizontal arrow ($\Rightarrow$), which was present on only a randomly selected half of all trials, located in one of 10 semi-randomly selected possible locations around the circle. Participants were instructed to search for the target on each display and use their right hand to press “1” for present or “2” for absent. Target arrow location was counterbalanced between the top and bottom half of the screen. Non-target (distractor) arrows appeared in set positions around the circular array, oriented within some distribution of angles determined by the current task difficulty setting. OG task difficulty was manipulated on each probe by adjusting two parameters controlling the orientation of the distractor arrows: their minimum similarity to the target, and their similarity to other distractors. A minimum angular distance for distractor-to-target similarity was set to either 5, 15, 25, 45, 65, or 75 degrees. For distractor-to-distractor similarity, the maximum variance from the minimum angular distance was set to either

10, 20, or 40 degrees. The factorial combination of these parameters (excluding any combination where minimum plus variance could exceed the 90° vertical plane) created 15 difficulty conditions that gradually and monotonically changed in difficulty (see supplementary materials for OG task difficulty pilot study results). On every search display, each distractor arrow had a 50% chance of being randomly flipped across the horizontal plane and a 50% chance of being flipped across the vertical plane, so that distractor arrows could vary from horizontal across either 5-175° or 185-355°. In order to minimize uncontrolled pop-out effects, we ensured that no distractor arrow in the array was within 5 degrees of an arrow that appeared in the same location on the circle during the previous display. This manipulation ensured that each visual-search array was a completely randomized new array of possible targets and distractors.

PM Task Stimuli

Colored images of unfamiliar faces and unfamiliar scenes were gathered from various in-house and online sources. These images were controlled for valence and familiarity. Of those images, 230 (115 faces, 115 scenes) were selected for use in this experiment. For each participant, 40 faces and 40 scenes were randomly selected to serve as the PM targets, 75 faces and 75 scenes were used as distractors. PM target images did not appear as distractors and were used on one trial only. Distractor images never reappeared within the same trial, but later reappeared on subsequent trials (mean exposures per distractor = 14, min = 6, max = 20).

PM Task Description

Participants completed six blocks (five in the fMRI sample) of 20 trials each. Blocks were separated by brief rest periods, the length of which was determined by the participant. Five trials in each block were “catch trials” (containing fewer than 8 probes), which were included to keep participants engaged at the beginning of each trial. These short trials were included for the sole purpose of making sure that individuals did not ignore the PM-task component on early-trial probes. Performance on these catch trials was ignored, leaving 15 experimental (“real”) trials per block. PM and non-PM trials were randomly intermixed within each block, with one-third of all trials being non-PM trials, and the other two-thirds were equally split between face- or scene-target PM trials. OG task difficulty was manipulated in five conditions: it could either (1) increase starting at the easiest difficulty (level 1), (2) increase starting at the median difficulty (level 8), (3) decrease starting at the hardest difficulty (level 15), (4) decrease starting at the median difficulty, or (5) remain fixed at the median difficulty. For the main analyses reported here, the first two conditions were combined as “*increasing*” trials, the second two conditions were combined as “*decreasing*” trials, and the fifth condition was referred to as “*fixed*”. Changes in difficulty occurred at the rate of one shift in difficulty level per probe until either the end of the trial or until a difficulty endpoint was reached. Each of the five difficulty types occurred three times throughout each block in pseudo-random order. Fifteen “real” trials corresponding to the 3x5 combinations of PM type (face/scene/non-PM) and OG difficulty type occurred once per block. Performance on face and scene trials was similar, so to increase statistical power, these trials were collapsed for subsequent analyses. The difficulty types for catch trials were

counterbalanced across the entire experiment. For more specifics about task design and the difficulty manipulation, see supplementary materials.

Each trial began with the presentation of the PM target (a face, a scene, or no target) for 3-sec, followed by a 1-sec fixation cross. For non-PM trials, participants saw a yellow null ($\emptyset$) sign in lieu of a face or scene. For PM trials, participants were informed that the PM target shown was only relevant for the current trial. After target presentation, participants saw a series of 1-15 probes per trial. Every probe contained a visual-search array in the center of the screen, with one face and one scene (each of size $9.5^\circ \times 9.5^\circ$ in visual angle) vertically aligned with the center of the images placed 11.5° above or below the search array. Each probe was on the screen for 2 sec, during which the participants were allowed 1.9s to respond to the presence or absence of the horizontal arrow in the OG task, or to indicate whether the PM target had reappeared. They were instructed to equally weight the importance of both tasks, and only one response (to either the OG task or the PM task) was allowed per probe (“task-switch” approach⁷⁴). Trial lengths were predetermined and pseudo-randomized so that every participant had the same number of total probes for face-target, scene-target, and non-PM trials. Scene and face locations were randomized on each probe, and faces and scenes appeared on the top or bottom of the display with equal probability. Visual feedback was presented immediately following each probe response, in the form of the arrows turning green for correct OG responses, turning red for incorrect OG responses, or a yellow border surrounding the screen for PM false alarms. Probe feedback remained on screen for the remaining duration of each 2-sec probe. The 1.9 s response

deadline (of 2 s total probe length) ensured that some time (minimum 100 ms) was always devoted to feedback on every probe.

On trials with a PM target presented at the beginning of the trial (“PM trials”), participants performed both tasks as described above. On trials with no PM target presented (“non-PM trials”), participants were instructed to ignore the face and scene images and focus solely on the OG task. The PM target reappeared only once per trial, and its reappearance always marked the end of the trial. After the final probe of each trial, participants were given feedback on the PM task in the form of a green border appearing around the edge of the screen for correct PM responses and a red border for missed PM targets. This feedback (or a blank screen for non-PM trials) remained for 2s and was followed by a 6-s ITI with a fixation cross on the screen before the next trial began.

MRI acquisition and preprocessing

MRI data were acquired on a 3.0-T Siemens Skyra MRI scanner with a 32-channel head coil. Whole brain, high-resolution anatomical images were collected for registration and parcellation using a T1-weighted MPRAGE sequence (repetition time (TR) = 1900ms, echo time (TE) = 2.43ms, flip angle = 9°, field of view (FOV) = 256x256x192, 1mm isotropic voxels). Functional images were acquired using a T2*-weighted multiband accelerated EPI pulse sequence (TR = 2s, TE = 29ms, flip angle = 78°, FOV=76x76, slice-thickness = 3mm, multiband factor = 2, number of slices = 48, no gap). Following shim correct at the beginning of each scan session, a B0 field-map with the same slice prescription as the functional data was acquired.

As an initial step for preprocessing, DICOMs were converted to NIFTI format using dcm2niix⁷⁵. Next, Freesurfer's⁷⁶ recon-all function was used to skull strip and parcellate the high-resolution anatomical image. MRI data was preprocessed using a combination of Freesurfer 6.0, FSL 5.0.9⁷⁷, and ANTs 2.1.0⁷⁸ functions. Functional images were first slice time corrected using FSL's slicetimer function. Then, functional runs were normalized to the third run of the main task (middle run) using a combination of within-run motion correction, rigid and affine registration, and field unwarping processes from FSL and ANTs. Non-linear registration, via antsRegistrationSyn, was then used to correct for between run differences. Lastly, high pass filtering (128s) was applied to the images. Multivariate pattern analyses were then performed within this registered subject space, independently for each participant (for more MVPA details, see the supplementary materials).

For the univariate GLM analysis, rigid and affine transformations were used to register the functional scans to the high-resolution anatomical, and then non-linear transformations were applied to normalize runs to the MNI-template. These images were spatially smoothed (5 mm gaussian), but no further preprocessing was performed before using FSL FEAT for modeling. The model included separate regressors for the PM target presentation, PM trial probes 1 to n-1, probe n (when the PM target reappeared in PM trials), non-PM trial probes 1 to n, trial-feedback, and rest. Six motion parameters, extracted using FSL's MCFLIRT, were included as confound regressors. FSL's FEAT was used to identify voxels that were more responsive on PM trials (PM+OG) than on non-PM (OG-only) trials (cluster correction, $p < .001$; see supplementary materials).

This group level results map was then individually transformed from standard space into subject functional space using the inverse normalization parameters used for mapping subject functional to anatomical scans and the anatomical scans to the MNI template, and then used as an initial feature selection mask for multivariate pattern classification analysis. A classifier was trained (using the Princeton MVPA toolbox, <https://github.com/princetonuniversity/princeton-mvpa-toolbox>) to distinguish between TRs with face PM targets, scene PM targets, no-PM target (OG task only), and rest. For each k-fold iteration, we used data from the three face/scene/rest localizer training blocks and two OG/rest localizer training blocks (see supplementary materials), as well as four of the five PM task blocks for further feature selection and training. One PM task block was held out on each fold for testing.

For all analyses involving RTs, we excluded any responses faster than 300 ms. This criterion is in line with previous work^{69,79} and was used in order to exclude late responses carried over from the preceding response window. Because this paradigm involves long PM trials (mean 28s, range 8-36s), it produced few behavioral PM reports per participant. Therefore, to increase statistical power for this analysis, we performed a non-parametric bootstrap analysis using data sampled from all participants. On each bootstrap iteration (n=10000) of this analysis, 78 participants were selected at random with replacement and combined to make one super subject. We used logistic regression to test the relationship between PM accuracy and PM cost slope and/or PM intention evidence on the different trial types. The stability of the effects across all iterations was analyzed to assess population-level reliability.

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