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Proactive Control Processes in Event-Based Prospective Memory: Evidence From Intraindividual Variability and Ex-Gaussian Analyses

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The present study implemented an individual differences approach in conjunction with response time (RT) variability and distribution modeling techniques to better characterize the cognitive control dynamics underlying ongoing task cost (i.e., slowing) and cue detection in event-based prospective memory (PM). Three experiments assessed the relation between proactive control ability, ex-Gaussian parameter estimates (μ and τ), intraindividual variability in responding (coefficient of variation, CoV), and PM cue detection. Experiment 1 examined these relations using a standard nonfocal PM paradigm. Experiments 2 and 3 further assessed how PM importance and PM cue focality, respectively, influenced performance. Across all experiments, nonfocal PM was associated with increases in all cost measures, but only μ reliably predicted cue detection. Importance instructions and focal PM cues selectively increased and decreased μ cost, respectively, relative to the standard nonfocal condition. These findings suggest that μ cost may reflect a target-checking process that benefits cue detection and produces slowing throughout the entire ongoing task. Additionally, across all experiments proactive control was positively associated with μ cost and cue detection, and generally negatively associated with variability cost (τ and CoV). These findings suggest that natural variation in proactive control ability may affect reliance on more efficacious monitoring processes that facilitates cue detection. Furthermore, variability in responding may have little influence on successful PM. The results from the current study highlight the utility of RT variability and distribution analyses in understanding PM costs and have important implications for extant theories of PM concerning the cognitive control processes underlying cue detection.

Keywords: prospective memory, proactive control, attention, ex-Gaussian function, intraindividual variability

Supplemental materials: http://dx.doi.org/10.1037/xlm0000489.supp

Event-based prospective memory (PM) refers to relying on environmental cues to trigger retrieval of a deferred action plan from long-term memory. Perhaps one of the most reliable PM finding is that *cost* to ongoing task processing (e.g., slower responding) often occurs as a result of possessing an intention for future action relative to when the same task is performed with no intention (Einstein & McDaniel, 2010; Smith, Hunt, McVay, & McConnell, 2007). Observed costs suggest that some capacity-consuming cognitive control process has been enacted to support PM cue detection and action retrieval (Marsh, Hicks, Cook, Hansen, & Pallos, 2003). Despite the abundance of research investigating the conditions under which PM control processes are active (e.g., McDaniel & Einstein, 2000), relatively little is known about the *nature* of these control processes or the *regularity* in which they are enacted. Thus, in the current study we take a novel individual differences approach in conjunction with response time (RT) variability and distribution modeling to examine the role of proactive control processes in PM monitoring and cue detection.

PM Monitoring

In a typical event-based PM task, after completion of a baseline measure of performance on a particular ongoing task (e.g., lexical-decision task) participants form an intention to perform a specific action (e.g., press "/" key) upon encountering specific cues (e.g., TOR syllable) during the subsequent ongoing task. One widely demonstrated finding is that cost to ongoing task processing (e.g., slower responding) often occurs as a result of possessing an intention (Smith et al., 2007). Most contemporary theories of PM share the assertion this cost suggests that resource-demanding attentional processes are necessary to monitor the environment for PM cues and this monitoring reduces available executive resources to support ongoing task processing (Heathcote et al., 2015; Marsh et al., 2003; but see Strickland, Heathcote, Remington, & Loft,

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2017). However, current theories differ in their supposition on whether or not capacity-consuming attentional control processes are always necessary for successful PM retrieval (see Einstein & McDaniel, 2010; Smith, 2010).

The preparatory attentional and memory (PAM) process theory posits that costly, preparatory monitoring processes are required to determine whether or not the current stimulus requires a PM response (Smith, 2003; Smith et al., 2007). The two-process model of strategic monitoring assumes that cost may arise from maintenance of a mental task set that treats ongoing task stimuli as potential PM retrieval cues as well as periodic target checks to determine whether the current trial contains intention-relevant details (Guynn, 2003, 2008; Guynn, McDaniel, & Einstein, 2001). These preparatory processes are thought to be frontally mediated and produce ongoing task cost regardless of the nature of the intention (Brewer, Knight, Marsh, & Unsworth, 2010; Burgess, Quayle, & Frith, 2001; McDaniel, LaMontagne, Beck, Scullin, & Braver, 2013). In contrast, the Multiprocess Framework additionally posits that PM retrieval can sometimes occur spontaneously. Spontaneous retrieval is thought to be hippocampally mediated and does not require executive attention processes for intention retrieval (Brewer et al., 2010; Gordon, Shelton, Bugg, McDaniel, & Head, 2011). That is, spontaneous retrieval processes can automatically elicit retrieval of the intention without cost to ongoing task processing (Cohen & Gollwitzer, 2008; Einstein & McDaniel, 2005; Knight et al., 2011; but see Smith et al., 2007). Consistent with this idea, considerable research has demonstrated that high rates of PM retrieval can occur in the absence of ongoing task cost during focal processing conditions, whereas nonfocal cue detection is typically lower and comes at a cost to ongoing task performance (Einstein & McDaniel, 2005).

An interesting find was that there is considerable overlap between the cognitive control processes proposed by the Multiprocess Framework to underlie PM retrieval and those proposed by the dual mechanisms of control (DMC) framework to explain cognitive control in various attention tasks (see Bugg et al., 2013 for a more detailed discussion). The DMC framework proposes that cognitive control operates via two distinct modes, referred to as *proactive* and *reactive* control (Braver, 2012; Braver, Gray, & Burgess, 2007). Similar to working memory, proactive control is involved in actively maintaining context information (e.g., task instructions, previous stimuli, cues, etc.) to optimally bias perception and action systems to facilitate goal-directed behavior. Proactive control is a top–down, early selection process that serves to anticipate and prevent interference by sustaining activation of goal-relevant attentional states (Braver et al., 2007). In contrast, reactive control occurs via transient activation of bottom–up, late-correction processes that serve to reduce interference after its onset. Thus, both proactive control and preparatory attention involve sustained activation of a mental task set that biases attention toward goal-relevant information, whereas both reactive control and spontaneous retrieval involve transient activation of goal-relevant information triggered by particular characteristics of the stimuli. Accordingly, it has been hypothesized that proactive control processes may underlie nonfocal cue detection, whereas reactive control processes may be sufficient for focal cue detection (Braver, 2012; Bugg et al., 2013; Bugg, McDaniel, Scullin, & Braver, 2011; see also Shelton & Scullin, 2017) for a related discussion on top-down and bottom-up influences on PM.

In contrast to the aforementioned attention-based theories of nonfocal PM costs, a recent theory has been proposed that suggests that costs do not reflect allocation of resource-demanding attentional processes away from the ongoing task to support prospective remembering. This Delay Theory instead posits that costs arise because the PM intention competes for response selection with the more routine ongoing task. Because PM information (e.g., whether the stimulus contains syllable TOR) is suggested to accrue more slowly than ongoing task information (e.g., stimulus lexicality), participants must, therefore, delay ongoing task responding to allow more time for PM evidence to accumulate in an effort to avoid missing cues (Heathcote et al., 2015; Loft & Remington, 2013). The Delay Theory therefore suggests that possessing an intention causes participants to respond more cautiously to increase the likelihood that the PM response (e.g., '/' key) is selected before the ongoing task response (e.g., "word"). Although this account argues that attentionally demanding monitoring processes are not needed to successfully respond to PM cues, it is suggested that individuals with greater executive capacity (e.g., working memory capacity) may be more likely to sufficiently delay responding to facilitate prospective remembering (Strickland et al., 2017). Thus, both the preparatory attention and delay accounts suggest that proactive control may underlie nonfocal PM costs, albeit for different for reasons. One of the primary aims of the current study was to examine how proactive influences PM performance. However, using traditional measures of central tendency for cost estimates may not fully capture the regularity in which proactive control processes are enacted to support cue detection.

Beyond the Mean

The traditional approach of analyzing mean RTs is useful because it provides a great deal of information in a single summary statistic and requires minimal statistical sophistication to derive. However, RT distributions in the psychological sciences are almost uniformly positively skewed by slower responses (Luce, 1986) and interpretative problems can arise when using measures of central tendency to describe data that is not normally distributed. Reliance on mean RTs may also mask systematic variations in cognitive processes that contribute to the observed RT distributions. Consequently, there has been considerable recent interest in implementing alternative techniques to examine RTs in PM, and in cognitive tasks more generally.

Recent evidence has accumulated suggesting that intraindividual variability (IIV) in responding across tasks is predictive of a variety of higher-order cognitive processes (Unsworth, 2015). The coefficient of variation (CoV; *SD*/mean), a measure of *inconsistency*, is a type of IIV that reflects fluctuations in RTs on a trial-by-trial basis and accounts for variability in responding beyond overall changes in mean RT (as there is typically a linear relationship between mean RT and *SD*; Wagenmakers & Brown, 2007). Considerable evidence suggests an increase in IIV may be indicative of variation in attention control, whereby periodic lapses of attention produce slowing on a subset of trials (Duchek et al., 2009; Jackson et al., 2012; Tse et al., 2010; Unsworth, 2015; Unsworth, Redick, Lakey, & Young, 2010; West, 2001). For example, Unsworth (2015) demonstrated that IIV across a variety of attention control tasks (e.g., antisaccade, flanker, and Stroop), but not across nonattention demanding tasks (i.e., lexical decision), was predictive of a variety of executive and fluid abilities (e.g., working memory capacity, fluid intelligence, and long term memory), subjective reports of mind-wandering, and everyday attention and memory failures. That is, individuals with better executive abilities were less likely to lapse attention during these attention control tasks as indicated by reduced IIV. These findings suggest that RT variability may be an important indicator of one's ability to maintain attention during a given task.

An alternative means to examine the underlying cognitive processes that contribute to observed RTs is to fit a mathematical function to raw RT distributions. The ex-Gaussian function has been shown to provide a good fit to empirical RT distributions across a wide variety of cognitive tasks (Andrews & Heathcote, 2001; Luce, 1986; Ratcliff, 1979; Spieler, Balota, & Faust, 1996).[1] The ex-Gaussian function is a convolution of the Gaussian and Exponential distributions. Three parameters are obtained from ex-Gaussian analyses: μ and σ, which reflect the mean and *SD* of the Gaussian distribution, respectively, and τ, which reflects the mean of the Exponential distribution. Important for understanding the relation between ex-Gaussian parameter estimates and mean RTs, the sum of μ and τ estimates is approximately equal to the mean RT because the sum of the true values of μ and τ is equal to the true mean of the ex-Gaussian distribution. Because of this property, it is possible for a variable to produce an increase in τ while also decreasing μ (or vice versa), thereby creating a null effect on the observed mean RT (e.g., Balota et al., 2008; Spieler et al., 1996). Figure 1 illustrates that an increase in μ leads to a distributional shift to the right, an increase in σ produces distributional spreading, and an increase in τ leads to a positive distributional skew (see Balota & Yap, 2011 for more details on RT distribution analyses).

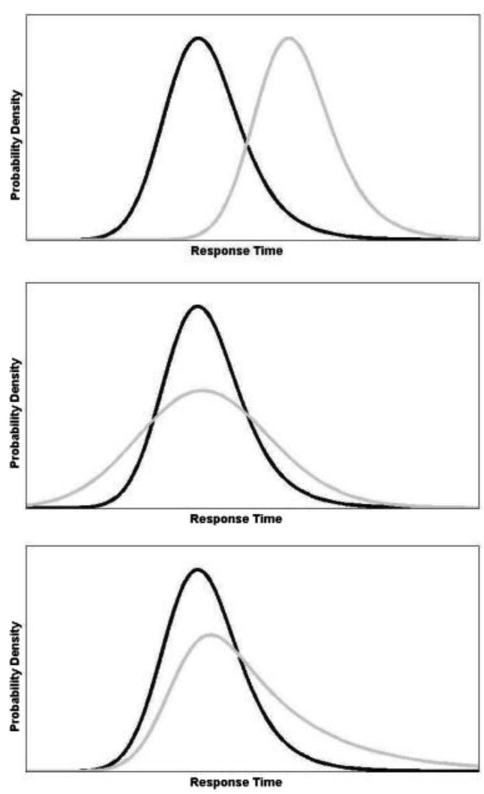

Figure 1. Two hypothetical distributions with changes (gray line) only in μ (top), σ (middle), or τ (bottom).

Although it is important to note that ex-Gaussian parameters do not reflect underlying cognitive processes (see Matzke & Wagenmakers, 2009), it has been suggested that the Gaussian component may reflect lower order peripheral/automatic processes, whereas the exponential component may reflect higher order central/controlled and decision-related processes (Hohle, 1965; but see Luce, 1986). For example, changes in μ are often found in attention control tasks that produce interference effects because of competition for response selection (De Jong, Berendsen, & Cools, 1999; Spieler, Balota, & Faust, 2000; Unsworth, Spillers, Brewer, & McMillan, 2011). In contrast, and similar to the CoV measure, increases in τ are negatively associated with various executive abilities (e.g., working memory) and are thought to reflect goal neglect because of periodic lapses of attention (Schmiedek et al., 2007; Tse et al., 2010; Unsworth et al., 2010, 2011). More important, these findings suggest that theorizing of the underlying cognitive control processes that contribute to PM cost may be improved by disentangling the components of the RT distribution rather than simply relying on mean RT measures.

Beyond the Mean in PM

Only a handful of studies to date have examined the relationship between RT IIV/distributional parameters and PM monitoring/cue detection (Abney, McBride, & Petrella, 2013; Ball, Brewer, Loft, & Bowden, 2014; Brewer, 2011; Ihle, Ghisletta, & Kliegel, 2016; Loft, Bowden, Ball, & Brewer, 2014; McBride & Abney, 2012; Rummel, Smeekens, & Kane, 2016; Unsworth, 2015). In regard to IIV, Ihle et al. (2016) derived IIV measures from the *SD* of ongoing task RTs during nonfocal and focal PM tasks. Consistent with the idea that nonfocal, but not focal, cue detection requires executive attention, only nonfocal IIV cost was predictive of cue detection and other measures of cognitive control abilities (e.g., working memory capacity, inhibition). These findings suggest that periodic attentional lapses can be detrimental to cue detection. In contrast, Unsworth (2015) found no relation between CoV derived from attention control tasks and nonfocal cue detection. The reason for the discrepant findings across the two studies is not entirely clear, but likely reflects how the IIV measures were derived (i.e., from PM tasks vs. attention control tasks) and the exact measure used (i.e., *SD* vs. CoV). As described previously, assessing only the *SD* in responding does not account for the linear relationship between mean RT and *SD* and, thus, the results by Ihle et al. may simply reflect a general slowing phenomenon (and this effect may be exacerbated by the inclusion of older adults in their sample, who generally exhibit processing speed deficits).

[1] There are numerous other mathematical functions that have received considerable empirical investigation that may be more appropriate to use depending on a priori assumptions of the underlying distribution that generated the empirical data, including the Wald, Gamma, Weibull, and Lognormal functions (Heathcote, Brown, & Cousineau, 2004; Matzke & Wagenmakers, 2009; Ulrich & Miller, 1993; Van Zandt, 2000).

In regard to ex-Gaussian analyses, Brewer (2011) originally fit the ex-Gaussian function to RTs during a nonfocal PM task. Somewhat surprisingly, RT distributions provided little evidence that the observed cost from possessing an intention was because of monitoring processes that were enacted fairly continuously throughout the task, as would be indicated by an overall shift in the modal portion of the distribution (i.e., μ). That is, an overall shift in the distribution should have been observed if participants were engaging an additional processing step (e.g., a target check) on each trial that hypothetically took 100 ms to complete. Instead, ex-Gaussian analyses revealed that the cost was due entirely to an increase in the relative frequency of slow responses (τ; see also Ball et al., 2014). This finding suggests that PM-relevant slowing only occurred on a subset of trials. However, more recently Loft et al. (2014) found that nonfocal cost was due increases in both μ and τ. Regarding functional relations to successful prospective remembering, however, only μ was predictive of nonfocal cue detection (see also Ball et al., 2014). This latter finding is particularly important, as it is not entirely clear why μ, but not τ, cost would be predictive of cue detection if only a single process was contributing to ongoing task cost. Based on these findings, it was suggested that PM cost may arise because of PM processes enacted fairly continuously throughout the task that produces general slowing across all trials (i.e., μ) in conjunction with transient processes that produces additional slowing on a subset of trials (i.e., τ). Furthermore, general slowing across all trials appears to be most important for successful intention fulfillment. However, because only recently have RT IIV/parameter estimates been implemented to better understand the cognitive control processes involved in PM, with mixed results, more research is needed to determine whether various portions of the RT distribution are meaningfully associated with cognitive control processes that may facilitate PM.

In addition to the aforementioned analytic techniques, a growing body of research has fit evidence accumulation models to PM ongoing task data (Ball & Aschenbrenner, 2017; Boywitt & Rummel, 2012; Heathcote et al., 2015; Horn, Bayen, & Smith, 2011; Horn & Bayen, 2015; Strickland et al., 2017). Evidence accumulation models (e.g., diffusion model, linear ballistic accumulator model; Brown & Heathcote, 2008; Ratcliff, 1978) simultaneously account for speed *and* accuracy of ongoing decisions and allow for the dissociation of different cognitive processes thought to contribute to the ongoing task decision process. These processes include the rate of information accumulation (drift rate), the amount of evidence required to make a decision (boundary separation), and peripheral processes occurring either before or after the actual decision (nondecision time). The primary finding from this literature is that PM costs are largely associated with increased decision boundaries (see Heathcote et al., 2015 for a more detailed discussion). Additionally, manipulations thought to influence the degree of monitoring enacted (e.g., importance of intention, cue frequency, and cue focality) produce changes in nondecision time (Ball & Aschenbrenner, 2017; Horn & Bayen, 2015). Based on these findings, it has been suggested that PM costs may reflect a joint combination of increased response caution (reflected in boundary changes) as well as target-checking occurring before or after the decision (reflected in nondecision time). However, because the current study was not designed to fit evidence accumulation models to the data, we reserve a more detailed discussion of these effects until the General Discussion.

Current Study

Prior research has indicated that executive control processes are related to RT variability measures, and these same processes have been thought to underlie successful PM performance (e.g., Brewer et al., 2010; Marsh & Hicks, 1998; Smith & Bayen, 2005). However, little research has examined the functional role of monitoring costs on cue detection and the cognitive processes underlying this cost. The current study, therefore, examined individual differences in proactive control ability in conjunction with RT IIV/distributional analyses to better characterize the attention processes that give rise to PM cost and their functional role in cue detection. Experiment 1 served as an initial investigation of IIV and ex-Gaussian analyses underlying PM cost and the role of proactive control in PM using a standard nonfocal PM paradigm. Experiments 2 and 3 adopted a quasi-experimental design approach to more directly examine hypotheses regarding changes in monitoring processes and RT measures across conditions that placed more or less demands on executive attention. Experiment 2 examined how emphasizing the importance of the PM intention, which has been shown to increase cue detection at the cost of ongoing task performance (Ball & Aschenbrenner, 2017; Horn & Bayen, 2015; Kliegel, Martin, McDaniel, & Einstein, 2004; Loft, Kearney, & Remington, 2008; Smith & Hunt, 2014), influenced RT measures and whether these changes were moderated by proactive control ability. Experiment 3 examined whether there was a potential cost to relying on proactive control, namely in a focal processing condition in which intention retrieval can occur spontaneously (i.e., without cost). Across all studies, we assessed the relation between proactive control, RT measures, and cue detection to try to provide a more nuanced understanding of the cognitive processes that give rise to successful PM.

Experiment 1

Recent studies examining IIV and ex-Gaussian parameters in the context of PM have yielded mixed findings (e.g., Brewer, 2011; Loft et al., 2014; Ihle et al., 2016; Unsworth, 2015). Experiment 1, therefore, sought to better characterize the underlying processes that contribute to nonfocal RT cost using multiple measures of PM and proactive control ability to achieve more reliable indicators of the constructs of interest. The two PM tasks were common nonfocal tasks used in the literature in which participants performed a control (no intention) and PM (with intention) block to derive measures of cost and cue detection. To assess proactive control ability, we used two versions of the AX-continuous performance task (AX-CPT; Braver et al., 2007). In this task, a "target" response is required only when the probe *X* follows the cue *A* (AX trial), which occurs on the majority of the trials (e.g., 70%) to produce expectancy relative to all other trials types (e.g., 30% of trials are AY, BX, and BY). More important, on BX trials context information (the cue *B*) can be used to inhibit a dominant response tendency to make a target response when *X* is presented, whereas on AY trials context information (the cue *A*) serves to bias processing to subsequently (erroneously) make a target response. Thus, reliance on proactive control processes should facilitate performance on AX and BX trials, but can actually hurt performance on AY trials. Consistent with this idea, populations thought to have deficits in goal-maintenance abilities (e.g., low working memory capacity individuals, older adults) typically show impaired BX performance but relatively spared AY performance (Braver et al., 2001; MacDonald et al., 2005; Paxton, Barch, Racine, & Braver, 2008; Redick & Engle, 2011; Richmond, Redick, & Braver, 2015). These findings suggest that the AX-CPT may be useful in identifying individuals with deficits in proactive control, but relatively spared reactive control.

As proactive control is thought to reflect maintenance of context information (e.g., a PM intention), proactive control ability should be positively associated with nonfocal cue detection. In particular, in nonfocal cue conditions it is necessary to engage preparatory attention processes to engage target checks on each trial to determine whether a stimulus contains intention relevant details, which should produce slowing on all trials. Similarly, the Delay Theory suggests that individuals high in proactive control may adopt more conservative ongoing task response thresholds to allow more time for PM response selection to occur that should operate across all trials of the ongoing task (Strickland et al., 2017). Consequently, both the preparatory attention and response caution accounts predict that proactive control should exert an influence on the μ parameter, and this cost should be associated with better cue detection (Loft et al., 2014). For simplicity, we refer to the processes that should theoretically operate across all trials and influence the μ parameter as *continuous monitoring*.[2]

The predicted relation between proactive control ability, variability measures (IIV and τ), and cue detection is less clear. From the attention control domain, RT variability may reflect periodic lapses of attention that produces slowing on a subset of trials. Thus, it may the case that possessing an intention makes the ongoing task more difficult and, therefore, causes participants to more often periodically lapse attentional focus of maintaining the entire task set (ongoing task + PM task; but see Rummel et al., 2016). These lapses of attention should produce cost in the tail of the distribution, and this cost should be negatively associated with cue detection (Ihle et al., 2016). Additionally, those better at maintaining the task set (i.e., those high in proactive control ability) should show reduced RT variability. Alternatively, RT variability may actually instead reflect increased intention-relevant processing (e.g., target-checking) on a subset of trials. For example, if participants have the intention to respond to the "TOR" syllable, seeing the phoneme "OR" may stimulate target checks, and this target checking behavior should be functionally related to performance. Consequently, RT variability may actually be *positively* associated with cue detection. Finally, it may be the case that RT variability reflects a combination of both intention-irrelevant (periodic attentional lapses) and intention-relevant (periodic target checks) processes and, therefore, no relation between RT variability and cue detection should be observed (e.g., Loft et al., 2014).

Method

Participants. There were 169 Arizona State University undergraduate students who enrolled in an introductory psychology course participated in the study. Students received course credit for their participation in the study. As part of a larger scale study, over the course of two sessions (1.5 hr each), participants completed two nonfocal PM tasks (animal and 'TOR'), two proactive control tasks (verbal and spatial AX-CPT), two working memory tasks (operation and reading span), two inhibition tasks (antisaccade and flanker), and two vigilance tasks (psychomotor vigilance and degraded mask). However, for the purposes of the current study, we focus only on the relationship between PM and proactive control.[3] Twenty-one participants were excluded for missing data in one or more of the four tasks (the majority of which was because of participants not returning for Day 2).[4] Additionally, one multivariate outlier identified using Mahalanobis' distance was removed from all analyses. Thus, the final sample consisted of 147 participants.

Proactive control tasks.

Verbal continuous performance task (PC_{verb}). The PC_{verb} task used in the current study was based on Redick and Engle (2011) as described previously. Participants used their right hand to make target responses to the letter X when it followed an A (probes on AX trials) with the right index finger and to make nontarget responses to all other stimuli that appeared (all cues and probes on AY, BX, and BY trials) with their left index finger. Letters were presented for 500 ms each, and participants had up to 1,000 ms from the onset of each letter to respond. Cues and probes were randomly determined for each nontarget. The cue—probe and intertrial intervals each lasted 1,000 ms. Participants completed practice blocks until they had achieved a mean probe accuracy of 75% before proceeding to the experimental blocks. There were a total of four experimental blocks, with a brief resting period in between each block. Within each block there were 40 cue-probe trials, with 28 AX trials (70%), 4 BX trials (10%), 4 AY trials (10%), and 4 BY trials (10%). Proactive control scores were calculated by computing the difference between proportional AX trial hits and BX trial false alarms. This measure was chosen as the dependent variable because previous research has suggested that working memory differences primarily arise for BX (and to a lesser degree, AX) trials (MacDonald et al., 2005; Redick & Engle, 2011).

Spatial continuous performance task (PC_{spat}). The procedure for the PC_{spat} task was identical to the PC_{verb} task. The only difference between the two tasks was that dots patterns in various spatial arrangements were used as cues and probes rather letters (see MacDonald et al., 2005 for more details). Valid cue and probe trials are displayed in Figure 2, along with several examples of invalid cue and probe trials. Target responses were required only when the valid probe was presented after the valid cue, which

[2] Because "monitoring" generally refers to the strategic deployment of attention to support prospective remembering, it not typically associated with response caution in terms of the Delay Theory.

[3] As the purpose of the current study was primarily to assess the role of proactive control processes in prospective memory, for brevity and clarity we elected to only report analyses that included the proactive control tasks. However, full task details and analyses that include all individual differences constructs can be found in Experiment 1 of the dissertation by Ball (2015).

[4] The data reported in the dissertation by Ball (2015) consisted of 169 participants in which missing data imputation was conducted on missing cells. However, for reproducibility we elected to exclude those participants in the current study. The exclusion of these participants did not significantly alter any results and the interpretation of the findings is similar regardless of whether or not these participants are included.

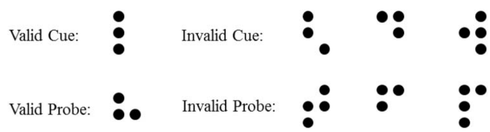

Figure 2. Examples of valid and invalid cue and probe trials during the spatial continuous performance task.

occurred on the majority of the trials (70%). Other than the stimuli being dot patterns, the materials and procedure was identical to the PC_{verb}. Proactive control scores were calculated by computing the difference between proportional AX trial hits and BX trial false alarms.

PM tasks.

Animacy judgment task (AJT). For the animacy judgment task (AJT), participants decided on each trial whether the presented word was living (e.g., fish) or not living (e.g., table). During the practice, control (before intention formation), and experimental (after intention formation) blocks there were 30, 70, and 210 trials, respectively, half of which were living and half of which were nonliving. The 310 separate words were chosen from the Kucera and Francis (1967) norms. All of these stimuli were randomly assigned to a trial position within the experimental sequence for each participant tested. After this randomization, the software randomly assigned eight PM cues to Trials 25, 50, 75, and so forth, through Trial 200. Each of the cues contained the syllable “tor” (e.g., doctor) and were chosen from the MRC database (Coltheart, 1981).

Participants read instructions for the experiment from the computer monitor. Ongoing task instructions for the practice, control, and experimental blocks informed participants that they were to respond (using the F and J keys) according to whether or not the word on a trial was living or not living. After each decision was made, a *waiting* message would appear to indicate to the participants to press the spacebar to continue to the next trial. After receiving instructions for the AJT, participants performed a 30 trial practice block followed immediately by a 70 trial control block. After completion of the control block, participants were informed that in a few minutes they would perform the AJT again. Additionally, they were instructed that if at any point during the AJT they encounter a word containing the syllable “tor,” they should make their animacy judgment per usual but then press the “/” during the waiting message instead of pressing the spacebar. After participants acknowledged that they understood the task instructions, they performed a 10-min antisaccade task before beginning the experimental block so that the intention was not fully active when the experimental AJT was administered. After completion of the 210 trial experimental AJT block participants were queried for their memory of the PM instructions. Participants that were unable to describe the nature of PM intention were replaced and not included in any analyses, as this reflects a retrospective memory error rather than a PM error.

Syllable judgment task (SJT). The procedure for the SJT with an “animal” intention (e.g., horse) was nearly identical to the AJT. For the SJT task, participants decided on each trial whether the presented words contained one (e.g., hat) or two (e.g., peanut) syllables. For the practice, control, and experimental blocks, 310 words (not used in the AJT) were chosen from the Kucera and Francis (1967) norms. After completion of the control block, participants were informed that they would later again perform the SJT and that if at any point during the subsequent SJT they encounter a word that denoted an animal (e.g., horse), they should make their syllable judgment per usual but then press the “/” during the waiting message instead of pressing the spacebar. After participants acknowledged that they understood the task instructions, they performed a 10-min flanker task before beginning the experimental block so that the intention was not fully active when the experimental SJT was administered. After completion of the 210 trial experimental SJT participants were queried for their memory of the PM instructions. Participants that were unable to describe the nature of PM intention were replaced and not included in any analyses.

Response time analyses. Only correct (noncue) trials within 2.5 *SD*s of each participant’s mean were included for the analyses. We also excluded the two trials after cue presentation in the experimental blocks because participants may have been still been engaging cue-related processes during these trials. RTs were analyzed by calculating mean RTs during the ongoing task for each participant, separately for control and experimental blocks for both PM tasks. CoV (*SD*/mean RT) measures were calculated on the same RTs separately for control and experiment blocks. Ex-Gaussian analyses were performed on the same RTs using Quantile Maximum Probability Estimation (QMPE) software (Heathcote et al., 2004) to obtain parameters estimates for each participant that best produced the observed data. Estimates of μ, σ, and τ were derived separately for control and experimental blocks for each participant using the maximum possible number of quantiles (N-1). Acceptable model fits were obtained within 30 iterations for all participants. Reliabilities for the ex-Gaussian measures can be found in the supplemental material.

Vincentile plots. Vincentile plots allow for examination of the raw RT distribution across conditions without making assumptions about the underlying shape of the distribution (Andrews & Heathcote, 2001). Vincentiles were separately computed for each task by rank ordering raw RTs from shortest to longest for each individual (separately for each ongoing task block) and calculating the mean of the first 20%, the second 20%, and so forth. These figures display the best-fitting predicted vincentiles superimposed on the observed vincentiles. Vincentiles for each ongoing task phase and the difference between the two can be found in the supplemental material. The minimal divergence between the predicted and observed vincentiles suggests that the data were well fit by the ex-Gaussian function, and the plotted cost measures are largely consistent with the ex-Gaussian analyses.

Results

PM performance. Descriptive statistics for each measure can be found in Table 1. Averaging across both PM tasks, overall participants detected a little over half of the PM cues (M = .62, SE = .02). For RT measures, there was significant cost because of possessing an intention, with faster mean RTs in the control block (M = 817, SE = 12) than the PM block (M = 936, SE = 13), $F(1, 146) = 188.69$, $p < .001$, $\eta_p^2 = .564$. CoV also increased from the control (M = .31, SE = .01) to the PM (M = .34, SE = .01) block, $F(1, 146) = 57.63$, $p < .001$, $\eta_p^2 = .283$. Additionally, there was an increase in all ex-Gaussian parameters because of possessing an

Table 1
Descriptive Statistics for Proactive Control and Prospective Memory Tasks

Task	DV	Mean	*SE* Mean	Min	Max	Skew	Kurtosis
PC_{VERB}	*d′*	2.59	.09	−.95	4.69	−.11	.01
PC_{SPAT}	*d′*	2.52	.09	−1.03	4.69	−.38	.26
AJT	PM	.67	.02	.00	1.00	−.87	.02
AJT	RT_{CB}	812	11	552	1,331	.75	1.01
AJT	RT_{PMB}	1051	16	624	1,633	.56	.40
AJT	RT_{COST}	239	11	−168	631	.37	.63
AJT	CoV_{CB}	.31	.01	.14	.67	1.03	1.93
AJT	CoV_{PMB}	.38	.01	.17	.71	.82	1.62
AJT	CoV_{COST}	.07	.01	−.19	.33	−.21	.74
AJT	MU_{CB}	558	5	441	685	.25	−.27
AJT	MU_{PMB}	645	7	452	914	.56	.38
AJT	MU_{COST}	87	6	−63	361	1.04	1.57
AJT	TAU_{CB}	257	9	49	671	.94	1.24
AJT	TAU_{PMB}	408	12	114	913	.87	.89
AJT	TAU_{COST}	151	9	−220	512	.14	1.20
AJT	$SIGMA_{CB}$	56	2	.36	138	.46	.03
AJT	$SIGMA_{PMB}$	85	3	11	224	1.01	1.94
AJT	$SIGMA_{COST}$	29	3	−57	155	.52	.73
SJT	PM	.58	.03	.00	1.00	−.58	−.76
SJT	RT_{CB}	821	16	468	1,457	1.04	1.26
SJT	RT_{PMB}	820	14	485	1,463	1.13	2.03
SJT	RT_{COST}	−.46	9	−384	301	−.45	.55
SJT	CoV_{CB}	.31	.01	.13	.68	.66	.62
SJT	CoV_{PMB}	.31	.01	.16	.54	.55	−.09
SJT	CoV_{COST}	.00	.01	−.22	.15	−.37	.05
SJT	MU_{CB}	554	7	397	845	.74	.94
SJT	MU_{PMB}	558	7	405	989	1.58	5.90
SJT	MU_{COST}	5	5	−153	157	−.06	−.18
SJT	TAU_{CB}	270	12	72	860	1.49	2.59
SJT	TAU_{PMB}	264	10	76	664	1.28	1.95
SJT	TAU_{COST}	−7	8	−345	223	−.63	1.37
SJT	$SIGMA_{CB}$	58	3	.01	210	1.31	2.91
SJT	$SIGMA_{PMB}$	62	2	20	241	2.99	18.99[a]
SJT	$SIGMA_{COST}$	3	2	−95	69	−.60	.27

Note. DV = dependent variable; PC = proactive control; AJT = animal judgment task; SJT = syllable judgment task; PM = cue detection; RT = reaction time; CoV = coefficient of variation; CB = control block; PMB = prospective memory block; cost = prospective memory block-control block.
[a] The large Kurtosis was driven by one participant with a large σ value. However, removing this participant did not significantly alter any results and was, therefore, included in all analyses.

intention: μ was smaller in the control (M = 556, SE = 5) than PM (M = 602, SE = 6) block, $F(1, 146) = 109.79$, $p < .001$, $\eta_p^2 = .429$; τ was smaller in the control (M = 264, SE = 9) than PM (M = 336, SE = 10) block, $F(1, 146) = 115.86$, $p < .001$, $\eta_p^2 = .442$; σ was smaller in the control (M = 57, SE = 2) than PM (M = 73, SE = 2) block, $F(1, 146) = 59.97$, $p < .001$, $\eta_p^2 = .291$.

Proactive control and PM measures. Correlations between each of the proactive control, cue detection, and RT cost (PM block—control block) measures can be found in Table 2. As can be seen, other than for CoV performance across all measures within a construct was positively correlated. Thus, a composite score was calculated from the means of the two measures for each construct.

Individual differences in PM performance. Correlations between the composite proactive control, cue detection, and RT cost measures can be found in Table 3. As can be seen, proactive control was positively correlated with cue detection and μ cost, but not with mean RT, IIV, or τ cost. Only mean RT and μ were predictive of cue detection.

Discussion

The results from Experiment 1 suggest that cost because of possessing an intention was associated with increases in IIV (Ihle et al., 2016) and all ex-Gaussian parameter estimates (Loft et al., 2014). Individuals higher in proactive control ability, as measured by performance on the AX-CPT, were more likely to detect PM cues and exhibited greater μ cost. Furthermore, μ cost was positively associated with cue detection (Ball et al., 2014; Loft et al., 2014). These findings suggest that individuals with higher scores on the proactive control tasks tended to exhibit slowing across the majority of the ongoing task trials. Thus, individual differences in context maintenance are associated with individual differences in slowing in PM tasks, which likely influences the probability that an individual will accidentally miss a cue.

In contrast to predictions, however, proactive control was not associated with RT variability measures (IIV or τ). As described previously, increases in RT variability because of possessing an intention may reflect both PM-independent (e.g., attention lapses)

Table 2
Correlations Between Proactive Control, Prospective Memory Cue Detection, and Prospective Memory Cost Measures

DV	PC_{VERB}	PC_{SPAT}	PM_{SJT}	PM_{AJT}	RT_{SJT}	RT_{AJT}	CoV_{SJT}	CoV_{AJT}	MU_{SJT}	MU_{AJT}	TAU_{SJT}	TAU_{AJT}	$SIGMA_{SJT}$	$SIGMA_{AJT}$
PC_{VERB}	1.00													
PC_{SPAT}	.60**	1.00												
PM_{SJT}	.14	.18*	1.00											
PM_{AJT}	.22**	.20*	.26**	1.00										
RT_{SJT}	.13	.11	.26**	.07	1.00									
RT_{AJT}	.07	−.01	.16	.23**	.37**	1.00								
CoV_{SJT}	.01	.08	.01	.03	.52**	.12	1.00							
CoV_{AJT}	.01	−.09	.09	−.08	−.01	.39**	−.10	1.00						
MU_{SJT}	.17*	.07	.25**	.04	.56**	.26**	−.26**	.12	1.00					
MU_{AJT}	.20*	.17*	.14	.34**	.31**	.56**	.14	−.33**	.22**	1.00				
TAU_{SJT}	.06	.08	.16	.06	.84**	.28**	.79**	−.07	.04	.23**	1.00			
TAU_{AJT}	−.04	−.11	.10	.06	.24**	.85**	.05	.69**	.17*	.04	.18*	1.00		
$SIGMA_{SJT}$	.07	.03	−.05	−.13	.01	.19*	−.29**	.10	.40**	.10	−.24**	.18*	1.00	
$SIGMA_{AJT}$	.15	.13	.05	.11	.17*	.25**	.15	−.21*	.12	.68**	.12	−.13	.09	1.00

Note. DV = dependent variable; PC = proactive control; AJT = animal judgment task; SJT = syllable judgment task; PM = cue detection; RT = reaction time; CoV = coefficient of variation. Values for prospective memory reaction time measures reflect cost (PM block-control block).
* $p < .01$. ** $p < .05$.

and PM-specific (e.g., periodic target checks) processes. It was reasoned that proactive control may serve to reduce attentional lapses, or alternatively, reduce periodic reactive target checks (because presumably high proactive control participants are already making them on a consistent basis). One possible explanation for this null relation is that proactive and reactive control are thought to reflect independent processes (Gonthier, Braver, & Bugg, 2016), which is not captured in our criterion measure from the AX-CPT (i.e., proactive control was measured on a continuous basis). Thus, high ability participants may not necessarily "lapse" attention as often as low ability participants, but may nevertheless periodically engage reactive control processes (e.g., upon encountering the phoneme "OR") that produce additional slowing on a subset of trials. Consequently, both high and low ability participants may similarly exhibit increases in τ, albeit for different reasons. However, we readily admit this is a post hoc explanation of the current findings. More important, RT variability measures were unrelated to cue detection, a pattern that is replicated in subsequent experiments. This suggests that variability in responding in the context of PM tasks may reflect random noise that does not necessarily influence cue detection.

Table 3
Correlations Between Proactive Control and Prospective Memory Constructs

DV	PC	PM	RT	CoV	μ	τ	σ
PC	1.00						
PM	.26**	1.00					
RT	.10	.27**	1.00				
CoV	.00	.03	.45**	1.00			
μ	.22**	.31**	.66**	−.17*	1.00		
τ	−.02	.16***	.87**	.70**	.20*	1.00	
σ	.15***	.01	.27**	−.12	.59**	−.02	1.00

Note. DV = dependent variable; PC = proactive control; AJT = animal judgment task; SJT = syllable judgment task; PM = cue detection; RT = reaction time; CoV = coefficient of variation. Values for prospective memory reaction time measures reflect cost (PM block-control block).
* $p < .01$. ** $p < .05$. *** $p < .08$.

It should be noted that, somewhat surprisingly, cost was not evident in the syllable judgment PM task with an animal intention. The reason for this is not readily apparent, although prior studies have demonstrated monitoring is more difficult for syllable than word cues (Scullin, McDaniel, Shelton, & Lee, 2010). More important, though, despite no cost in the SJT there was still a significant correlation between cost measures (except COV) in the two PM tasks (see Table 2). This finding suggests that the observed cost may reflect a stable individual difference trait, such that individuals who respond more slowly in one task also tend to respond more slowly in a conceptually similar, but methodologically different, task.

Taken together, the results from Experiment 1 replicate and extend previous research examining response time distributions garnered from PM tasks. These results suggest that context maintenance abilities are associated with increased μ cost, and this cost produces better cue detection. However, the relation between proactive control and RT variability is less clear. In Experiments 2 and 3 we aimed to systematically manipulate variables that should influence proactive control processes to explore potential causal relations with PM monitoring.

Experiment 2

The findings from Experiment 1 suggest that proactive control may be an important predictor of whether or not participants engage continuous monitoring processes to support PM retrieval. In Experiment 2 we, therefore, examined whether encoding instructions could increase reliance on more efficacious monitoring. Prior research has shown that emphasizing the importance of the PM intention facilitates subsequent cue detection relative to standard encoding instructions, but this comes at a cost to ongoing task performance (Horn & Bayen, 2015; Kliegel et al., 2004; Loft et al., 2008; Smith & Hunt, 2014). It has also been shown that importance instructions are particularly beneficial older adults (Ball & Aschenbrenner, 2017; Hering, Phillips, & Kliegel, 2014; but see Smith & Hunt, 2014), and this population has deficits in proactive control (Braver et al., 2001; Paxton et al., 2008). Importance instructions may, therefore, be particularly beneficial for low proactive control ability participants in the current study. One possibility is that emphasizing the importance of the PM intention may serve to increase target-checking behavior (Ball & Aschenbrenner, 2017; Horn & Bayen, 2015), or induce more cautious responding (Heathcote et al., 2015; but see Horn & Bayen, 2015), making it less likely to accidentally initiate the prepotent ongoing task response instead of a PM response. This would result in an increase in μ in the importance relative to standard encoding condition. Alternatively, importance instructions may help individuals maintain attentional focus throughout the task, thereby reducing periodic lapses of attention as evidenced by decreased RT variability.

Method

Participants. There were 270 Arizona State University undergraduate students who enrolled in an introductory psychology course (that did not participate in Experiment 1) participated in the study. Students received course credit for their participation in the study. Participants were randomly assigned to the standard (N = 131) or importance (N = 139) PM encoding conditions. All participants completed two proactive control tasks (verbal and spatial AX-CPT) and a nonfocal PM task.

Materials and procedure. All participants first performed the PM task (standard or importance), followed by the verbal and spatial proactive control tasks. The proactive control tasks (verbal and spatial AX-CPT) were identical to those of Experiment 1. The PM task was identical to the animacy judgment PM task ('TOR' intention) used in Experiment 1, except that between the control and experimental blocks participants instead performed a brief (1–2 min) questionnaire as a distractor task. The only difference between the two PM conditions was that following the standard PM instructions, participants in the importance condition were additionally instructed that "performance on the PM task (i.e., detecting cues) was more important than doing well on the ongoing task (i.e., speed/accuracy)" (Kliegel et al., 2001).

Results

Proactive control. Performance on the two continuous performance tasks was positively correlated in both the standard, r = .604, $p < .001$ and importance, r = .576, $p < .001$ conditions. A composite proactive control measure was therefore calculated from the d' scores of both tasks.

Individual differences in PM. As can be seen in Table 4, in the standard condition we largely replicate results from Experiment 1. Proactive control was positively correlated with cue detection and μ cost, and μ cost (but not variability cost) was correlated with cue detection. In addition, as originally hypothesized proactive control was negatively correlated with CoV and τ cost.

Influence of encoding instructions. For the subsequent analyses, PM variables of interest were separately submitted to a generalized linear model with condition (standard vs. importance) as a between-subjects variable and proactive control ability entered as a covariate. Because possessing an intention produced a significant increase in all RT measures (all ps < .05), for simplicity the dependent variable for RT analyses was the cost measure (PM block—control block).[5] All analyses were conducted on the entire set of participants, and means for each measure can be found in

Table 4
Correlations Between Proactive Control and Prospective Memory Task Measures in Standard (Below Diagonal) and Importance (Above Diagonal) Conditions

DV	PC	PM	RT	CoV	MU	TAU	SIGMA
PC	1.00	.19*	.01	.04	.00	.02	−.04
PM	.29**	1.00	.13	−.12	.32**	−.03	.17*
RT	−.12	.16	1.00	.39**	.60**	.88**	.42**
CoV	−.21*	−.08	.33**	1.00	−.28*	.65**	−.14
MU	.16***	.22*	.52**	−.43**	1.00	.15***	.62**
TAU	−.22*	.07	.88**	.62**	.06	1.00	.16
SIGMA	.06	.08	.38**	−.22*	.67**	.09	1.00

Note. DV = dependent variable; PC = proactive control; RT = mean RT cost; CoV = coefficient of variation cost; MU = μ cost; TAU = τ cost; SIG = σ cost. Correlations below the diagonal reflect the standard condition, whereas those above diagonal reflect the importance condition.
* $p < .01$. ** $p < .05$. *** $p < .08$.

Table 5. In the case of any significant interactions with proactive control ability, for ease of interpretation performance is compared across the subset of participants falling in the upper (high) and lower (low) 25% of the proactive control ability distribution for each condition (Aiken, West, & Reno, 1991).

Cue detection. Cue detection was better in the importance than standard condition, $F(1, 266) = 12.84$, $p < .001$, $\eta_p^2 = .046$, and for those higher in proactive control ability, $F(1, 266) = 16.74$, $p < .001$, $\eta_p^2 = .059$. However, there was no interaction between the two, $F(1, 266) = 1.16$, $p = .283$, $\eta_p^2 = .004$. Thus, high proactive control ability participants detected more cues in both the importance and standard condition.

Mean RT cost. The analysis of mean RT cost failed to reveal any significant effects, Fs < 2.52, ps > .113.

CoV cost. There was no CoV cost difference between conditions, $F(1, 266) = 3.05$, $p = .082$, $\eta_p^2 = .011$, and no effect of proactive control ability, $F(1, 266) = 1.82$, $p = .178$, $\eta_p^2 = .007$. However, there was a significant interaction between the two, $F(1, 266) = 4.22$, $p = .041$, $\eta_p^2 = .016$. This interaction primarily reflects that while there was no CoV difference between low (M = .04, SE = .02) and high (M = .05, SE = .02) ability participants in the importance condition, there was greater cost for low (M = .10, SE = .02) than high (M = .03, SE = .02) ability participants in the standard condition.

Mu cost. There was greater μ cost in the importance than standard condition, $F(1, 266) = 12.19$, $p = .001$, $\eta_p^2 = .044$. However, there was no effect of proactive control ability no interaction between the two, Fs < 1.51, ps > .220.

Tau cost. Similar to the CoV analysis, there was no τ cost difference between conditions and no effect of proactive control ability, Fs < 2.40, ps > .123. Additionally, there was a marginal interaction of condition and proactive control ability, $F(1, 266) = 3.42$, $p = .066$, $\eta_p^2 = .07$. As with the CoV analysis, this interaction primarily reflects that while there were no τ differences between low (M = 186, SE = 31) and high (M = 179, SE = 29) ability participants in the importance condition, there was greater cost for

[5] Effect size estimates for all block effects can be found in the supplemental material.

Table 5
Cue Detection and Reaction Time Measures (SE) Across Phases for Each Condition

Block	Condition	RT	CoV	μ	τ	σ	PM
Control	Standard	927 (14)	.35 (.01)	615 (5)	315 (13)	61 (2)	—
	Importance	958 (14)	.37 (.01)	610 (6)	352 (12)	56 (3)	—
PM	Standard	1,135 (19)	.41 (.01)	661 (8)	477 (15)	76 (3)	.72 (.02)
	Importance	1,198 (21)	.41 (.01)	689 (9)	511 (16)	86 (3)	.81 (.02)
Cost	Standard	208 (14)	.06 (.01)	46 (6)	161 (12)	15 (4)	—
	Importance	240 (15)	.04 (.01)	79 (7)	160 (12)	30 (4)	—

Note. RT = reaction time; CoV = coefficient of variation; PM = proportion of cues detected.

low (M = 198, SE = 28) than high (M = 123, SE = 16) ability participants in the standard condition.

Sigma cost. Similar to the μanalysis, there was greater cost in the importance than standard condition, $F(1, 266) = 7.02$, $p = .009$, $\eta_p^2 = .026$, but no effect of proactive control ability and no interaction between the two, $F\text{s} < 1$.

Discussion

The results from Experiment 2 are consistent with previous research demonstrating that importance instructions increase cue detection (Horn & Bayen, 2015; Kliegel et al., 2004; Loft et al., 2008; Smith & Hunt, 2014). Somewhat surprisingly, however, the increase in cue detection following importance instructions did not come at a cost to mean RTs. However, ex-Gaussian analyses showed that importance instructions actually increased μ cost relative to standard encoding instructions, and that this cost was correlated with cue detection. In contrast, although possessing an intention did increase RT variability, this cost was not associated with cue detection and did not differ between conditions. These findings again demonstrate that RT variability produces little influence on cue detection and additionally suggest that importance instructions do not serve to reduce attentional lapses. Rather, these findings suggest that importance instructions may facilitate cue detection by increasing continuous monitoring processes (e.g., target checking, response caution) that produces slowing across all trials.

In regard to proactive control ability, the results are consistent with those of Experiment 1 in that high proactive control ability participants detected more PM cues. Contrary to predictions, however, importance instructions did not benefit low ability participants to a greater extent than high ability participants (for similar results with older adults see Smith & Hunt, 2014). This may reflect that importance instructions increased μ, but not differentially for low and high ability participants. In contrast, importance instructions did reduce RT variability to a greater extent for low ability participants, but as with Experiment 1, this RT variability was not functionally related to cue detection. Together these findings suggest that individuals high in proactive control ability are more likely to respond more slowly to ensure that they do not miss cues, and that importance instructions serve to produce overall slowing regardless of proactive control ability. Proactive control ability may also serve to reduce periodic lapses of attention, but these lapses do not appear to significantly affect cue detection.

Experiment 3

Experiments 1 and 2 demonstrated that proactive control processes might be important in engaging continuous monitoring processes that contributes to cue detection. However, reliance on continuous monitoring processes may not always be efficacious, particularly under conditions that do not require costly monitoring processes. Previous research has demonstrated that high levels of cue detection typically occur during focal processing conditions and often occurs without the engagement of costly cognitive control processes (Einstein & McDaniel, 2005). Experiment 3, therefore, examined the role of proactive control abilities on cue detection and cost during focal processing conditions. Based on prior research demonstrating no focal cue detection differences as a function of working memory capacity (e.g., Brewer et al., 2010), we expected no differences in cue detection between high and low proactive control participants during focal processing conditions. However, if high proactive control participants are unable to regulate their monitoring strategies and continue to engage continuous monitoring processes, these individuals may be more likely to exhibit μ cost despite that fact that monitoring is unnecessary.

Method

Participants. There were 167 Arizona State University undergraduate students who enrolled in an introductory psychology course (that did not participate in Experiments 1 or 2) participated in the study. Students received course credit for their participation in the study. All participants completed two proactive control tasks (verbal and spatial AX-CPT), one nonfocal PM task, and one focal PM task.

Materials and procedure. The proactive control tasks (verbal and spatial AX-CPT) were identical to those of Experiment 2. Additionally, the practice, control, and nonfocal experimental blocks of the PM task were identical to those of the standard condition in Experiment 2 (i.e., animacy judgment with 'TOR' intention). The only difference was the inclusion of a focal PM block in which participants were instructed to press the "/" key any time the words "packet" or "dancer" appeared during the ongoing task followed. For the focal block, 210 new words were chosen from the Kucera and Francis (1967) norms. Each cue (packet, dancer) occurred four times and the order of presentation was randomly determined for each participant.

All participants first performed the practice and control phase of the PM task, followed by the two experimental blocks of the PM tasks (the order of which were counterbalanced across participants), and then the verbal and spatial proactive control tasks. For example, a participant would perform the tasks in the following order: PM practice phase, PM control block, questionnaire 1, nonfocal PM experimental block, questionnaire 2, focal PM experimental block, verbal AX-CPT, spatial AX-CPT. Upon completion of the first experimental PM block, participants were given instructions for the new PM task and told that the previous intention was no longer relevant.

Results

Proactive control. Performance on the two continuous performance tasks was positively correlated, $r = .630$, $p < .001$. A composite proactive control measure was, therefore, calculated from the d' scores of both tasks.

Individual differences in PM. As can be seen in Table 6 the results from the nonfocal condition completely replicate those from Experiment 1. Proactive control was positively correlated with cue detection and μ cost, and μ cost (but not variability cost) was correlated with cue detection.

Influence of cue focality. For the subsequent analyses, PM variables of interest were separately submitted to a generalized linear model with PM task (nonfocal vs. focal) as a within-subjects variable and proactive control ability entered as a covariate. All analyses were conducted on the entire set of participants, and means for each measure can be found in Table 7. In the case of any significant interactions with proactive control ability, for ease of interpretation performance was compared across participants falling in the upper (high) and lower (low) 25% of the proactive control ability distribution.

Cue detection. Cue detection was better in the focal than nonfocal condition, $F(1, 165) = 67.47$, $p < .001$, $\eta_p^2 = .290$, and for those higher in proactive control ability, $F(1, 165) = 7.74$, $p = .006$, $\eta_p^2 = .045$. However, there was no interaction between the two, $F < 1$. Thus, those high in proactive control ability actually performed better on both focal and nonfocal tasks.

Mean RT cost. Although RT cost reliably differed from zero for both conditions (ps $< .001$), it was significantly greater in the nonfocal than focal condition, $F(1, 165) = 232.39$, $p < .001$, $\eta_p^2 = .585$. However, there was no effect of proactive control ability, $F(1, 165) = 2.18$, $p = .141$, $\eta_p^2 = .013$, and no interaction between the two, $F(1, 165) = 2.93$, $p = .089$, $\eta_p^2 = .017$.

CoV cost. Although CoV cost reliably differed from zero for both conditions (ps $< .001$), it was significantly greater in the nonfocal than focal condition, $F(1, 165) = 3.91$, $p = .05$, $\eta_p^2 = .023$. Although there was no effect of proactive control ability on cost, $F < 1$, there was a marginal interaction between the two, $F(1, 165) = 3.69$, $p = .057$, $\eta_p^2 = .022$. However, follow up comparisons with high and low ability participants revealed no significant effects.

Mu cost. Mu cost only reliably differed from zero in the nonfocal condition ($p < .001$), and was significantly greater in the nonfocal than focal condition, $F(1, 165) = 127.74$, $p < .001$, $\eta_p^2 = .436$. This finding suggests that the RT cost in the focal condition was not because of increases in μ. Although there was no effect of proactive control ability, $F(1, 165) = 1.95$, $p = .164$, $\eta_p^2 = .012$, there was a significant interaction between the two, $F(1, 165) = 19.24$, $p < .001$, $\eta_p^2 = .104$. This interaction primarily reflects that while there were no μ differences between high ($M = <23.6$, $SE = 50$) and low ($M = 0$, $SE = 51$) ability participants in the focal condition, $F < 1$, there was greater cost for high ($M = 66$, $SE = 61$) than low ($M = 30$, $SE = 59$) ability participants in the nonfocal condition.

Tau cost. Similar to the CoV analysis, τ cost reliably differed from zero in both conditions (ps $< .001$), but was significantly greater in the nonfocal than focal task, $F(1, 165) = 146.62$, $p < .001$, $\eta_p^2 = .471$. This finding suggests that the RT cost in the focal condition was primarily because of increases in τ. There was no effect of proactive control ability and no interaction between the two, Fs < 1.

Sigma cost. As with the μ analysis, σ cost only reliably differed from zero in the nonfocal condition ($p < .001$), and was significantly greater in the nonfocal than focal condition, $F(1, 165) = 25.30$, $p < .001$, $\eta_p^2 = .133$. Although there was no effect of proactive control ability on cost, $F < 1$, there was a significant interaction between the two, $F(1, 165) = 7.95$, $p = .005$, $\eta_p^2 = .046$. This interaction primarily reflects that while there were no σ differences between nonfocal ($M = 18$, $SE = 35$) and focal ($M = 10$, $SE = 30$) condition for low ability participants, there was greater cost in the nonfocal ($M = 24$, $SE = 35$) than focal ($M = -1$, $SE = 30$) condition for high ability participants.

Table 6
Correlations Between Proactive Control and Prospective Memory Task Measures in Nonfocal (Below Diagonal) and Focal (Above Diagonal) Conditions

DV	PC	PM	RT	CoV	MU	TAU	SIGMA
PC	1.00	.19*	.04	.09	−.06	.08	−.15
PM	.15*	1.00	−.05	−.04	−.05	−.03	.00
RT	.15*	.16*	1.00	.56**	.42**	.88**	.03
CoV	−.02	−.06	.46**	1.00	−.33**	.79**	−.24**
MU	.22**	.17*	.47**	−.38**	1.00	−.06	.46**
TAU	.04	.08	.86**	.75**	−.05	1.00	−.20**
SIGMA	.08	−.01	.25**	−.14	.55**	−.04	1.00

Note. DV = dependent variable; PC = proactive control; RT = mean RT cost; MU = μ cost; TAU = τ cost; SIG = σ cost. Correlations below the diagonal reflect nonfocal condition, whereas those above diagonal reflect focal condition.
* $p < .01$. ** $p < .05$.

Table 7
Cue Detection and Reaction Time Measures (SE) for Each Condition

DV	Control	Nonfocal	Focal	Cost_{NF}	Cost_{F}
PM	—	.77 (.02)	.92 (.01)	—	—
RT	914 (13)	1,079 (14)	951 (11)	165 (10)	37 (9)
CoV	.34 (.01)	.39 (.01)	.38 (.01)	.05 (.01)	.04 (.01)
μ	604 (5)	644 (6)	599 (4)	41 (5)	−5 (4)
τ	314 (11)	437 (11)	353 (9)	123 (9)	39 (8)
σ	56 (2)	71 (2)	59 (1)	16 (3)	4 (2)

Note. DV = dependent variable; PM = proportion of cues detected; RT = reaction time; CoV = coefficient of variation; NF = nonfocal condition; F = focal condition.

Discussion

The results from Experiment 3 are generally consistent with those from Experiments 1 and 2. High proactive control individuals were more successful at detecting cues and exhibited greater μ cost in the nonfocal condition than low proactive control participants. Additionally, greater nonfocal μ, but not RT variability, cost produced better cue detection. These findings again suggest that proactive control processes may be beneficial for engaging continuous monitoring processes to support cue detection during nonfocal processing conditions. More important, however, high proactive control participants did not appear to inappropriately engage continuous monitoring processes during the focal processing condition. Although there was cost in the focal condition, this cost was relatively nominal and due entirely to increases in τ. An interesting find was that this latter finding suggests that prior demonstrations of cost during focal conditions could simply reflect periodic lapses of attention rather than evidence for monitoring. Regardless, these findings suggest that high proactive control participants are able to appropriately disengage monitoring processes under scenarios that do not require costly monitoring.

Somewhat surprisingly, however, high proactive control ability participants had greater nonfocal *and* focal cue detection. This may reflect that the current study used two focal cues,[6] whereas typical focal processing conditions only present a single cue (e.g., Einstein & McDaniel, 2005; Scullin, McDaniel, & Einstein, 2010; Scullin, McDaniel, Shelton, & Lee, 2010). High proactive control participants may have, therefore, been better able to maintain multiple cues that facilitated cue detection. Alternatively, it may be that focal cue detection is not entirely automatic (Bugg et al., 2013). For example, Zuber, Kliegel, and Ihle (2016) found that individuals with higher inhibitory control ability detected more focal cues than low ability individuals. This suggests that inhibitory processes (e.g., inhibiting dominant ongoing task response) may be needed even during focal processing conditions. This is also consistent with prior research showing that focal cue processing does not completely eliminate age-related differences in cue detection (for meta-analyses see Kliegel, Jager, & Phillips, 2008; Uttl, 2008, 2011). As discussed previously, older adults have been shown to have deficits in proactive, but relatively spared reactive, control processes (e.g., Bugg, 2014; Paxton et al., 2008). Thus, it may be the case that some aspect of proactive control is nevertheless important for focal cue detection. However, additional research is needed to further validate these findings.

Table 8
Correlations Between Proactive Control and Prospective Memory Task Measures

DV	PC	PM	RT	CoV	MU	TAU	SIGMA
PC	1.00						
PM	.25**	1.00					
RT	−.02	.14**	1.00				
CoV	−.11*	−.08	.40**	1.00			
MU	.13**	.19**	.54**	−.35**	1.00		
TAU	−.10*	.05	.86**	.69**	.03	1.00	
SIGMA	.06	.04	.32**	−.18**	.65**	−.01	1.00

Note. DV = dependent variable; PC = proactive control; RT = mean RT cost; MU = μ cost; TAU = τ cost; SIGMA = σ cost.
$^{*}p < .01$. $^{**}p < .05$.

Cross-experimental analyses. Because the proactive control and nonfocal PM (AJT with "TOR" intention) tasks were identical across experiments, we examined the relation among proactive control and PM measures aggregated across all experiments that used the standard nonfocal PM task (AJT of Experiment 1, standard condition of Experiment 2, and nonfocal condition of Experiment 3; $N = 445$).[7] A new proactive control composite score was calculated based on the entire sample. As can be seen in Table 8, proactive control was positively correlated with both cue detection and μ cost, and negatively correlated with RT variability (CoV and τ). The null relationship between proactive control and mean RT cost, therefore, reflects that high ability participants produced more μ (less τ) cost and low ability participants produced more τ (less μ) cost, thereby producing a null effect in mean RT. This finding highlights the utility of implementing ex-Gaussian analyses (see also Balota et al., 2008; Spieler et al., 1996), as examining mean RT alone would suggest no systematic relation between proactive control and monitoring cost. Furthermore, ex-Gaussian analyses revealed that the correlation between mean RT and cue detection was because of increases in μ as a function of possessing an intention, as there was no relation between cue detection and τ cost.

Mediation analysis. The results from the current study suggest that proactive control is an important construct underlying monitoring and cue detection. However, the previous analyses do not fully capture the dynamic relation between proactive control and PM monitoring and detection processes. We, therefore, performed a mediation analysis to examine hypotheses regarding proactive control driving response time distribution components thereby leading to changes in successful PM remembering. Because only μ was related to both proactive control and cue detection, we restricted our analyses to μ cost. If proactive control is driving changes in μ thereby leading to individual differences in successful PM then we expect complete mediation. However, if there are additional processes driving μ we expect only partial mediation.

As can be seen in Figure 3, the mediation analysis revealed that proactive control was a significant predictor of μ (*a*), and μ was predictive of cue detection after controlling for proactive control (*b*). Furthermore, the indirect effect of proactive control on cue detection through μ (*ab*), although relatively small (accounting for 9% of the total effect [*c*]), was significant, indicating that mediation present. However, controlling for μ did not eliminate the relation between proactive control and cue detection (*c'*). Thus, μ only partially mediated the relation between proactive control and cue detection.

The results from the mediation analysis should be interpreted with caution given that small effects such as those seen here can be significant with such a large sample size. That being said, the finding that μ cost partially mediated the relation between proac-

[6] Two cues were presented in the focal condition because in the nonfocal condition (replicating the Experiments 1 and 2) four of the "TOR" cues were living (e.g., doctor), whereas four of the "TOR" cues were nonliving (e.g., tractor). Thus, we did not want participants in the focal condition to increase processing for only a single item type (e.g., living things) at the expense of the other item type (e.g., nonliving) if the only cue that was to appear was something living (e.g., doctor).

[7] A scatterplot matrix of the relations among variables, as well as the reliabilities for μ and τ, can be found in the supplemental material.

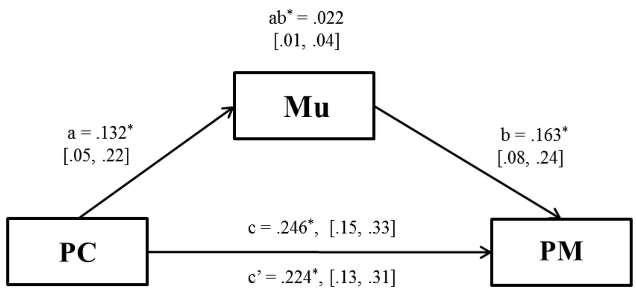

Figure 3. Mediation model for proactive control (PC), μ cost (μ), and cue detection (prospective memory, PM). Single-headed arrows connecting measures (squares) to each other represent standardized path coefficients indicating the unique contribution of the measures. Values in brackets reflect percentile bootstrap 95% confidence intervals. * $p < .01$.

tive control and cue detection is theoretically important. It is also the first study to our knowledge demonstrating that cognitive control ability can produce changes in ongoing task behavior (e.g., target-checking, response caution) that is functionally related to cue detection. However, the fact that proactive control only explained a small portion of the association between μ cost and cue detection suggests that there are other factors driving this relation that are not captured in the current study. Thus, future research is needed to provide a better understanding of the mechanisms that produce variation in ongoing task cost and ultimately lead to successful PM. The finding that proactive control was related to μ, but not mean RT, cost suggests that ex-Gaussian modeling may provide a useful means of further elucidating these mechanistic relations.

General Discussion

The lion's share of research on PM costs has been geared toward addressing theoretical debates about *when* cognitive control processes are enacted during event-based PM (e.g., Einstein & McDaniel, 2010; Smith, 2010; Smith et al., 2007). However, relatively little is known about the *nature* of these control processes and the *regularity* in which they are enacted. While the study of mean RT has undoubtedly contributed to our understanding of PM, we argue that these measures may not fully capture the underlying dynamics of PM monitoring processes involved in detecting cues and retrieving intentions. This point is particularly salient in the context of the current study where the interpretation of the results differs considerably depending on which cost metric was evaluated. Across all experiments, proactive control was positively correlated with cue detection but not associated with mean RT cost. From these findings alone, it would be tempting to conclude that the proactive control construct may be capturing attention or memory processes associated with PM that are independent of those that produce cost. However, ex-Gaussian analyses revealed that the null relation between proactive control and mean RT cost was because of increases in μ and decreases in τ for high relative to low proactive control participants. Together, these findings suggest that natural variation in proactive control ability may affect reliance on more efficacious monitoring processes that facilitate cue detection, and that RT distributional analyses may serve to improve current theorizing of the mechanisms underlying PM performance.

Ongoing Task Costs

Possessing an intention increased all RT measures across all experiments. While these findings are consistent with several recent studies fitting the ex-Gaussian function to RT data (e.g., Abney et al., 2013; Loft et al., 2014; Rummel et al., 2016), it is unclear whether RT distributional analyses necessarily provide new information if *all* parameters consistently change across manipulations (Cousineau, Brown, & Heathcote, 2004; Tse et al., 2010). For example, it is possible that possessing an intention could reflect a general slowing phenomenon whereby a single process (e.g., target checking, response caution) is slowed to different degrees at various portions of the RT distribution. More important, however, in Experiment 2 PM importance selectively increased μ cost relative to standard encoding instructions while τ cost remained unchanged. Additionally, in Experiment 3 focal processing conditions eliminated μ but not τ cost (although τ cost was greater in the nonfocal condition). Lastly, only μ cost reliably predicted cue detection across experiments (see also Loft et al., 2014). This latter finding is particularly interesting given that mean RT cost was not always reliably associated with PM performance (Experiment 2). Thus, although possessing an intention did produce changes in all parameters, only μ was sensitive to manipulations thought to influence the degree of monitoring enacted (i.e., importance, cue focality) and only μ cost reliably predicted PM performance. Together these findings suggest that μ cost may be an important indicator of PM-relevant slowing.

In regard to RT variability, it has previously suggested that this cost may reflect transient periods in which the intention periodically comes to mind that produces slowing on a subset of trials (Ball et al., 2014; Brewer, 2011; Loft et al., 2014). However, more recent research has suggested that RT variability may instead reflect period lapses of attention (Ihle et al., 2016; Unsworth, 2015). Based on these hypotheses, we reasoned that increased variability in the PM block should be positively correlated with cue detection in the former case, but negatively correlated with cue detection in the latter. Although there was a small positive association between RT variability and cue detection across all three experiments, this never reached conventional levels of significance. Although this does not align with either prediction, it is consistent with previous research showing no relation between RT variability and cue detection (Loft et al., 2014; Unsworth, 2015). However, it is unclear why we did not find a similar negative relation between RT variability and cue detection as Ihle et al. (2016).[8] It is possible that the n-back task used by Ihle et al. (2016) placed greater demands on attention control (and intention maintenance) and was, therefore, more sensitive to detecting attentional lapses that influenced cue detection. However, at least with the

[8] One potential reason for the negative relation between RT variability and cue detection by Ihle et al. (2016) is the use of *SD* as a measure of IIV does not account for the general processing speed of participants. We examined this possibility by comparing *SD* and cue detection collapsed across all experiments, but found no evidence to suggest that *SD* was predictive of performance ($r < .001$, $p = .99$).

tasks used in the current study, RT variability appears to be unrelated to cue detection.

In addition the null relation with cue detection, RT variability was not sensitive to manipulations thought to influence monitoring (i.e., importance, cue focality). Together these findings suggest that RT variability may not reflect transient periods of monitoring *or* lapses of attention. Alternatively, it could reflect some combination of both intention-relevant and intention-irrelevant processes that produces a null effect in the observed relation with cue detection. The primary issue with interpreting such a null effect is that PM paradigms are dual-tasks in nature (i.e., ongoing task + PM task), and so slowing could reflect processes associated with the ongoing task, the PM task, or some combination of both. What is clear from the current (and previous findings) is that possessing an intention *does* increase RT variability, which should be considered in any theory of PM costs. However, a question for future research is to examine how, or if, this RT variability is meaningfully associated with PM performance.

Cognitive Control Processes in PM

In addition to examining the influence of possessing an intention on cost measures, the current study sought to better understand the cognitive control processes that may underlie cost. The results suggest that proactive control may be an important process underlying PM monitoring, as higher proactive control ability was consistently associated with greater μ cost and less τ cost during nonfocal processing conditions that require strategic monitoring to facilitate cue detection. We are aware of only one other study that has examined proactive control in the context of event-based PM (but see Mahy et al., 2014 for a time-based PM task in children). Bugg et al. (2011) instructed participants to make a PM response any time the word *HORSE* appeared during a Stroop color-word naming task across blocks in which the Stroop trials were either mostly congruent (e.g., the word *RED* presented in the color red) or mostly incongruent (e.g., the word *RED* presented in the color green). In the Stroop task, correctly responding to the color of the stimuli on incongruent trials requires inhibiting the automatic tendency to read the words, and considerable research has demonstrated that the Stroop effect (i.e., congruent—incongruent RT) is larger during mostly congruent than mostly incongruent blocks (see Bugg & Crump, 2012 for a review). It is suggested that this proportion congruency effect occurs because during mostly incongruent blocks participants adopt a proactive control strategy to minimize interference because of frequent response competition from the irrelevant word dimension (Braver, 2012; Bugg, 2012; Gonthier et al., 2016). Consistent with the idea that proactive control was engaged to inhibit word reading in the mostly incongruent blocks, Bugg et al. found less Stroop interference and worse cue detection in the mostly incongruent relative to the mostly congruent blocks. That is, participants were less likely to detect the PM word cue in the mostly incongruent bock because attention was biased away from word reading. An interesting find was that in conditions using a spatial PM cue that was unrelated to the word-color naming task (e.g., respond to yellow box surrounding word), there were no differences in cue detection between proportion congruency conditions. We believe that a similar mechanism may be operating in the context of the current study, albeit to facilitate rather than hinder cue detection.

In the typical tasks used to examine PM costs, participants are instructed to perform the ongoing task as quickly or accurately as possible and, secondarily, to remember to make a different response on the infrequently presented PM cue trials. The dominant response tendency is therefore to quickly make an ongoing task response. Thus, much like in a mostly incongruent context of a Stroop task (Bugg et al., 2011), proactive control is needed during nonfocal processing conditions to optimally bias attention away from prepotent response tendencies (i.e., making ongoing task response), or to switch between the ongoing and PM task, to first engage target checks to determine whether the current stimulus contains intention-relevant details (Schnitzspahn, Stahl, Zeintl, Kaller, & Kliegel, 2013; Zuber et al., 2016). While such a processing mode would serve to increase ongoing task RTs, it also decreases the likelihood of accidentally missing PM cues. Therefore, we believe that the μ parameter may be sensitive to the increase in response competition produced by competing dual-task demands (i.e., ongoing task + PM task) and reflect increases in target-checking processes. Consistent with this idea, emphasizing the importance of the PM intention served to increase both cue detection and μ cost (albeit not differentially for high vs. low proactive control participants). Although proactive control may also serve to reduce attentional lapses, these lapses appear to have little influence on cue detection. Thus, individuals higher in proactive control ability appear to more effectively engage continuous target-checking processes that benefit cue detection.

The Relation Between RT Distributions and Evidence Accumulation Models

One issue with ex-Gaussian analyses is that the parameters derived from the model are purely descriptive indicators of the observed RT distribution (for correct trials). There should, therefore, be some caution in assigning specific cognitive processes to the observed parameters (see Matzke & Wagenmakers, 2009 for a more detailed discussion). However, the results from the current study clearly suggest that μ was sensitive to variables that influence the amount of monitoring enacted and reliably predicted cue detection across all experiments. Additionally, individual differences in proactive control were differentially associated with μ and τ parameters. We, therefore, believe that these results provide strong evidence that μ cost is a reliable indicator of PM-specific processing that is sensitive to individual differences in cognitive control ability. However, ultimately, RT distributional analyses should be coupled with specific computational models of task performance (e.g., evidence accumulation models). Unfortunately, the current study was not designed to fit such models to the observed data given the relatively small trial count (in the control block) and high accuracy during the ongoing task. Because evidence accumulation models account for both speed *and* accuracy, sufficient trial counts are needed for reliable estimates of both correct *and* incorrect RT distributions. However, it is still possible to provide some theoretical interpretation of ex-Gaussian parameters through their associations with parameters derived from the diffusion model.

As briefly described previously, the main parameters of the evidence accumulation models (e.g., diffusion model) are the rate of information accumulation (drift rate), the amount of evidence required to make a decision (boundary separation), and peripheral processes occurring either before or after the actual decision (nondecision time). It is important to note that although there is no one-to-one mapping of the parameters derived from the diffusion model and ex-Gaussian analyses, previous simulation studies have demonstrated that there are moderate relations among the two parameter types (Matzke & Wagenmakers, 2009; Schmiedek et al., 2007; Spieler, 2001). In particular, drift rate tends to be negatively related to μ and τ, boundary separation is positively related to μ and τ, and nondecision time is positively related to μ. In this regard, the increase in μ because of possessing an intention in the current study is consistent with increased boundary separation and/or nondecision time, whereas the increase in τ is consistent with increased boundary separation. Recent studies that have fit evidence accumulation models PM data have provided support for this interpretation.

Across several studies Horn and Bayen (2015) fit the diffusion model to PM ongoing task data. Across all experiments, nonfocal processing conditions were associated with increased boundary separation. This suggests that nonfocal intentions may cause participants to respond more cautiously during the ongoing task (Heathcote et al., 2015). Particularly relevant to the current study, it was also found that PM importance instructions and focal cues selectively increased and decreased nondecision time, respectively, relative to the standard nonfocal condition. Additionally, nondecision time predicted nonfocal cue detection (Experiment 1). Based on these findings, it was suggested that nondecision time cost may reflect increased target-checking frequency that occurred after PM importance or nonfocal (relative to focal) processing conditions. Similarly, we suggest that the increase in μ across various PM conditions in the current study may reflect the engagement of target-checking processes that are continuously enacted to support cue detection.

However, the Delay Theory offers an alternative explanation of the current findings. As described previously, the Delay Theory argues that PM costs do not reflect allocation of limited-capacity attentional resources away from the ongoing task to support prospective remembering. Rather, it is suggested that during PM blocks participants respond more cautiously to allow more time for PM-relevant information to accumulate. Consistent with this idea, Heathcote et al. (2015) found that possessing an intention selectively increased boundary separation (see also Strickland et al., 2017; but see Ball & Aschenbrenner, 2017; Horn & Bayen, 2015). As mentioned previously, a manipulation that only influences boundary separation (e.g., speed-accuracy instructions) should produce slowing of both the fastest and slowest RTs (Matzke & Wagenmakers, 2009; Ratcliff & McKoon, 2008). The finding in the current study that PM demands increased both μ and τ is, therefore, entirely consistent with Delay Theory.

More important, if the results of the current study can be accounted for by a single process (i.e., response caution), this would suggest that the distinction between "continuous" and "transient" processes contributing to ongoing tasks costs is unnecessary. However, it is not entirely clear how the Delay Theory can account for the entire set of results from the current study. If a single delay mechanism is producing cost, and this slowing is functionally related to cue detection (Heathcote et al., 2015; Strickland et al., 2017), it is unclear why μ but not τ would predict PM performance as slowing even in the tail of the distribution should theoretically benefit performance. Additionally, it is not clear how the Delay Theory accounts for the observed relations between proactive control and ex-Gaussian cost estimates. To provide a rationale for the wealth of research demonstrating a relation between working memory capacity and cue detection (e.g., Brewer et al., 2010; Marsh & Hicks, 1998; Smith & Bayen, 2005), Strickland et al. suggested that "low executive capacity" individuals may be less likely to increase "their thresholds in PM blocks" (p. 9). However, smaller boundary shifts in the PM block for low capacity individuals should result in less μ *and* τ cost than high capacity individuals, which was not the case in the current study. The alternative explanation by Strickland et al. that executive capacity may only be needed for cue trials is also inconsistent with the mediation analysis of the current study demonstrating that proactive control ability produced slowing (on noncue trials) that was functionally related to cue detection. Therefore, we find it difficult to understand how the Delay Theory (or any single-process model of PM costs for that matter) can account for the entire set of results from the current study. However, because the current study has a suboptimal data structure to fit evidence accumulation models, and because the ex-Gaussian parameters do not actually directly map onto accumulation model parameters (Matzke & Wagenmakers, 2009), we cannot rule out the alternative explanation of the current findings based on claims of the Delay Theory.

That being said, we are not arguing that such a delay strategy does not contribute to costs. Indeed, proactive control, which we argue should influence preparatory attention processes, only explained a small part of the association between μ and cue detection. It is therefore likely that multiple processes contribute to the observed cost and its functional role in cue detection including strategic delays in responding. In fact, at least one theory of PM monitoring suggests that multiple processes contribute to ongoing task cost. These processes include the maintenance of a prospective retrieval mode across the entire ongoing task as well as more intermittent target checks (Guynn, 2003). Additionally, individual differences research has demonstrated that a variety of cognitive processes contribute to cue detection, including working memory capacity, inhibition, and task switching, among others (Brewer et al., 2010; Rose, Rendell, McDaniel, Aberle, & Kliegel, 2010; Schnitzpahn et al., 2013; Smith & Bayen, 2005; Zuber et al., 2016). Notably, these studies have not focused on how such processes contribute to ongoing task cost (but see Smith & Bayen, 2005). Thus, the current study provides the first steps toward trying to better understand the regularity in which monitoring is enacted via RT variability and distributional analyses and the cognitive processes underlying this monitoring process. However, a fruitful avenue for future research would be to directly assess the relation between ex-Gaussian and evidence accumulation model parameters and their associations to different cognitive control abilities to better understand the processes that contribute to PM monitoring and cue detection.

Improving PM

The DMC framework posits that various situational and individual differences factors produce biases in reliance on proactive and reactive control processing modes in various cognitive control tasks (Braver, 2012). Consistent with this idea, the studies presented here demonstrated that situational (e.g., importance instructions, focal cue processing) and individual differences factors (i.e., proactive control ability) influenced reliance on proactive control processes in the context of PM. More important, however, reliance on proactive control processes appear to be mutable (increasing/decreasing μ cost after importance/focal cue instructions). This idea is consistent with previous PM theorizing that suggests that participants are sensitive to demands of the PM task and that they adjust their attentional-allocation policies accordingly to optimize performance (Marsh, Hicks, & Cook, 2005). An interesting find, though, high proactive control ability participants consistently outperformed low ability participants despite comparable changes in attention allocation as a function of different encoding instructions. This suggests that proactive control may have additional benefits to performance beyond monitoring. Consistent with this idea, μ cost only partially mediated the relation between proactive control and cue detection. Nonetheless, the current set of experiments suggest that proactive control variation may be useful for classifying which participants will rely on proactive monitoring processes during nonfocal processing conditions in which proactive control is optimal. Future experimental and individual differences will hopefully bring more theoretical clarity to the underlying cognitive control processes that support PM along with providing critical information for application focused PM interventions. Finally, although it is generally the case that τ is predictive of various performance across a variety of attention control studies (e.g., Schmiedek et al., 2007; Tse et al., 2010; Unsworth, Redick, Lakey, & Young, 2010; Unsworth et al., 2011), the results from the current set of studies suggest that identifying variables that influence μ may be most beneficial for understanding that mechanisms that contribute to PM.

Conclusions

The current set of studies used individual differences and quasi-experimental techniques in conjunction with RT variability/distributional analyses to provide novel insights about the nature of PM costs and the regularity in which cognitive control processes are enacted. PM costs occur in many different contexts and they lead to ongoing task decrements that may be detrimental to many aspects of healthy living. Accounting for the underlying cognitive control processes that create these costs can provide researchers with tools for developing strategic interventions that can facilitate ongoing task cognitive processing that is unrelated to PM while simultaneously improving PM abilities. Individual differences studies may also be useful for tailoring these interventions in nuanced ways that appropriately calibrate an individual's recognition of the situational factors and their reliance on the appropriate cognitive control strategies that will ultimately facilitate their PM abilities.

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