Evidence Accumulation Modeling of Event-Based Prospective Memory

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Introduction

The term Prospective Memory (PM) refers to the cognitive processes required to perform planned actions in the future. PM requirements are ubiquitous in everyday life, and in safety-critical occupations (Dismukes, 2012; Loft, 2014), and thus there is great value in thoroughly understanding PM processes. The current chapter focuses on *event-based* PM, in which the PM task is to respond to some future event or stimulus. Einstein and McDaniel (1990) devised a paradigm to study PM in the laboratory that has inspired nearly three decades of research. In that paradigm, participants perform their PM task in the context of an ongoing task (OT) (e.g., a lexical decision task, decide if strings of letters are words or non-words). Most trials are *non-PM trials*, in that they only require making OT decisions. Event-based PM paradigms require participants make PM responses to OT stimuli with PM target attributes (e.g., press '9' for any letter string that contains the syllable 'tor'). We refer to trials that present a PM stimulus as *PM trials*. This paradigm yields a measure of *PM accuracy*, the proportion of PM trials to which participants make their PM response. In addition to *PM blocks* of trials, which include the reviewed PM requirements, many studies include *control blocks* of trials, in which participants perform only the OT with no PM requirements. Often, response times (RTs) to non-PM trials in PM blocks are slower than in control blocks (Smith, 2003), an effect known as the *PM cost* to the ongoing task.

PM studies often involve observing a PM cost effect, or a difference in PM accuracy between differing PM conditions, and then formulating statements about PM processes to explain that. For example, the preparatory attentional and memory processes (PAM) theory (Smith, 2003) and the multiprocess view (MPV; McDaniel & Einstein, 2000) propose that PM cost is due to *capacity sharing* between monitoring for PM items and the OT. That is, they claim

that under PM conditions participants monitor the environment for PM targets, and this monitoring consumes cognitive capacity that would otherwise be dedicated to the processing required to make OT responses on non-PM trials, producing PM cost. Although this approach has been useful, there is more information available in the rest of the data, including not only the mean of each individuals' RT distributions, but also the variability and skew, as well as the relationships between RT and the proportion of each response observed (e.g., OT accuracy and PM accuracy). These data must to some degree be considered at the level of individual participants, and separately for each experimental design cell, to avoid drawing spurious conclusions based on artifacts of averaging (Estes & Maddox, 2005). Understanding such complex data requires computational models, which can reduce quantitative fits to every observed data point into measurements of psychological processes (Farrell & Lewandowsky, 2010; Myung & Pitt, 2002). In recent years, a number of studies have strived towards comprehensive accounts of data from the Einstein and McDaniel paradigm using *evidence accumulation models.* This chapter reviews these efforts, and what they have revealed about event-based PM.

Two evidence accumulation models have been applied in the PM literature: the linear ballistic accumulator model (LBA; Brown & Heathcote, 2008), and the diffusion decision model (DDM; Ratcliff, 1978). Both assume that once presented a stimulus, participants sample evidence towards the possible decisions they could make until evidence to a decision reaches threshold, determining the response made. Combined with some more specific assumptions, this enables the models to provide a complete account of many response choice and accuracy data. Fitting the models involves estimating the values of latent psychological quantities (i.e., parameters) that best account for the data, and examining how these latent quantities vary across

experimental manipulations. In both the LBA and DDM, the estimated parameters include *thresholds*, *accumulation rates*, and *non-decision times*. In the following section, we introduce the LBA, and discuss its' parameters. Although the LBA and DDM architectures differ, for the purposes of our discussion, the DDM threshold, accumulation rate, and non-decision time parameters have similar psychological interpretations to their LBA analogues which we discuss below.

The Linear Ballistic Accumulator

Before discussing how the LBA could accommodate PM paradigms (two OT responses and one PM response), we introduce the model as it applies to typical two-choice task (lexical decision). This is depicted in Figure 1. On each trial, participants run a separate evidence accumulator for each response (word, non-word). The accumulators start with some evidence drawn from a uniform distribution $U[0, A]$. Evidence then increases linearly over time towards threshold at some rate (v), drawn from a normal distribution. Accumulation rates, the speed at which evidence accrues towards each decision, are the locus of processing speed. They can increase with stimulus quality, for example they are higher with high frequency words in a lexical decision task (Brown & Heathcote, 2008). Rates are also linked to cognitive capacity devoted to a process, due to the theoretical connections between processing speed and capacity (e.g., Bundesen, 1990; Gobell et al., 2004; Kahneman, 1973; Navon & Gopher, 1979; Wickens, 1980). Recent empirical work justifies this, both by finding that rates agree with other measures of capacity (Donkin, Little, & Houpt, 2014; Eidels, Donkin, Brown, & Heathcote, 2010), and by manipulating capacity (e.g., adding a dual-task load) and observing that rates for a given accumulation process decrease when available capacity for that process decreases (Castro, Strayer, Matzke, & Heathcote, Under Review; Logan, Van Zandt, Verbruggen, & Wagenmakers,

2014). Two types of rate parameter are usually estimated when fitting the LBA: mean

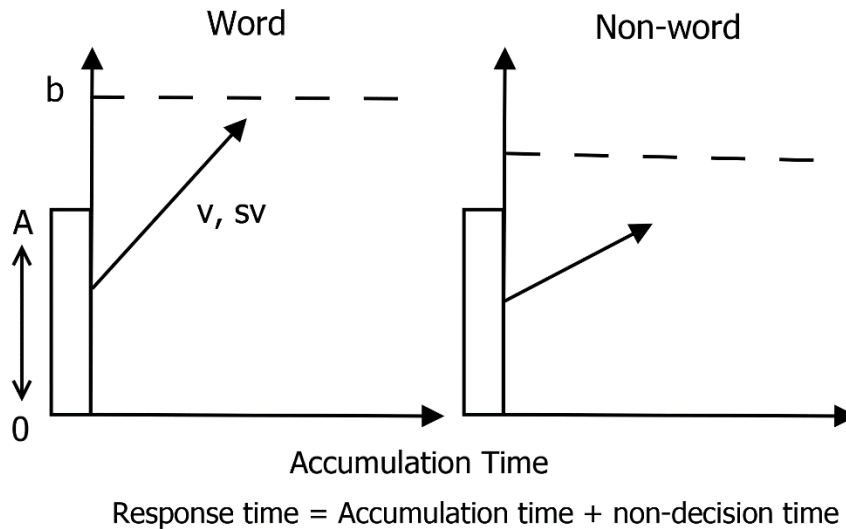accumulation rates, and trial-to-trial variability in accumulation rates.

Figure [6 – 1]. The Linear Ballistic Accumulator (Brown & Heathcote, 2008) as it would apply

to a two-choice lexical decision task. Evidence for both word and non-word decisions accrues to

threshold on each trial, and the first accumulator to reach threshold determines the response

made.

       The accumulator first to accrue total evidence equal to its threshold, *b,* determines the

response. Thresholds, the evidence required to make decisions, are generally considered the

locus of *a priori* strategy in evidence accumulation models, and as such are set prior to the

stimulus presentation. Decision time is equal to the total evidence required (threshold minus start

point) divided by the rate of the winning accumulator, and the total RT is given by this decision

time plus some *non-decision time*. Non-decision time includes the time to complete any process

that occurs outside of decision time, such as perceptual encoding and response execution.

Modeling of Prospective Memory Cost

Most PM studies collect few PM trials per participant. Thus, many studies do not model PM, and instead examine the latent processes underlying PM cost (Ball & Aschenbrenner, 2018; Boywitt & Rummel, 2012; Heathcote, Loft, & Remington, 2015; Horn & Bayen, 2015; Horn, Bayen, & Smith, 2011, 2013; Strickland, Heathcote, Remington, & Loft, 2017). To do so, they have modeled OT performance with the two-choice DDM and LBA, and examined how the model parameters differ under PM conditions as compared with control. We now review the findings of these studies.

PM cost is not caused by decreased ongoing task capacity. As accumulation rates index capacity, and PM cost was assumed to result from decreased capacity, the initial hypothesis was that PM cost would be caused by lower quality non-PM accumulation (Boywitt & Rummel, 2012; Horn et al., 2011). However, the weight of evidence indicates no effect of PM conditions on non-PM trial accumulation rates (Ball & Aschenbrenner, 2018; Heathcote et al., 2015; Horn & Bayen, 2015; Strickland et al., 2017), with the exception of one recent study (Anderson, Rummel, & McDaniel, 2018), which found decreased rates with PM in the DDM but not in a better-fitting LBA. These failures to find rate effects are inconsistent with previous theories, such as PAM and the MPV, which propose that PM cost results from PM usurping OT capacity. Note, however, that this finding only indicated that PM monitoring did not rely on OT capacity, it did not indicate that PM monitoring required no capacity at all. PM may rely on cognitive capacity that is not utilized under control conditions. Nonetheless, the finding that PM

cost was not a result of capacity sharing in the modeled paradigms called for an explanation of what did cause cost in those paradigms.

Increased thresholds underlie PM cost. All applications of the DDM to PM paradigms indicate that increased thresholds to make OT decisions are a substantial cause of PM cost (Anderson et al., 2018; Ball & Aschenbrenner, 2018; Boywitt & Rummel, 2012; Heathcote et al., 2015; Horn & Bayen, 2015; Horn et al., 2011, 2013; Strickland et al., 2017), and LBA modeling indicates thresholds are the only cause of cost (e.g., Heathcote et al., 2015; Strickland et al., 2017). To explain this, Heathcote et al. (also see Loft and Remington, 2013) proposed the delay theory of PM cost, which claims that participants raise OT thresholds so that on PM trials there is more time for the parallel PM process to reach threshold before the OT decision does. In contrast, Horn and Bayen (2015) claimed that OT threshold increases were a generic response to perceived task complexity, rather than being of direct benefit to PM. These theories may be compared with stimulus-specific PM tasks, in which the PM target feature only appears in one type of OT stimulus (e.g., a lexical decision task in which PM targets are always words). Under delay theory, with stimulus-specific PM participants might reason that only one OT decision would be likely to pre-empt the PM process (the one that is correct on PM trials) and adjust the threshold to that decision selectively. In contrast, if threshold increases owe to an increase in perceived task complexity, they would not be selective. Thus far, results have been mixed: Heathcote et al. did find evidence of selective threshold increases with stimulus-specific PM (higher word thresholds when the PM targets were only words), whereas Horn and Bayen did not (increases in both word and non-word thresholds when PM targets were only words). Our recent work revealed a mixture of strategies across participants (Strickland et al., 2017), and that after many trials threshold bias increases against the decision that competes with PM. This suggests

that some participants may not initially notice that one OT decision is more competitive with PM than the other, and instead learn it with task experience.

In the DDM, PM cost is also caused by increased non-decision time. The DDM attributes some PM cost to increased non-decision time. Some authors argue that this extra time contains a serial check for PM features either before or after each ongoing task decision (e.g., Horn & Bayen, 2015). Consistent with this, PM accuracy and non-decision time sometimes vary together. For example, Horn and Bayen and Anderson et al. (2018) both found that the magnitude of increases in non-decision time under PM conditions correlated across individuals with PM accuracy. In addition, Horn and Bayen found increased non-decision time when they emphasized to participants that PM was important, and also higher PM accuracy. Similarly, Anderson et al. (2018) found increased non-decision time and higher PM accuracy when they instructed participants to check for PM every trial.

Despite the above, the size of the increase in non-decision time seems small to include an entire PM decision, ranging between .02s and .09s. In addition, the non-decision time effects only arise with the DDM. The LBA has fitted better than the DDM to every PM cost data set where it has been applied, and has done so without including effects on non-decision time (Heathcote et al., 2015; Strickland et al., 2017). Simulations demonstrate that when a DDM is fitted to synthetic data generated from LBA threshold increases, it spuriously attributes some of those increases to non-decision time (Donkin, Brown, Heathcote, & Wagenmakers, 2011). Thus, the non-decision time component of PM cost may owe to the DDM mimicking a process better characterized by threshold increases. Consistent with this, one of the largest non-decision time costs observed (.08s) was in a 'boundary PM' condition, which instructed participants to raise their OT caution and *not* to look for PM items (Anderson et al. 2018). Further, a 'boundary

control' condition, which instructed OT caution but did not include a PM task, induced increases

in non-decision time that are fairly typical of PM conditions (.03s).

The Limitation of Inferring Prospective Memory Processes from Cost

Clearly, the above studies were illuminating regarding PM cost. They demonstrated that

many data sets containing PM cost did not indicate capacity sharing, and pointed to alternative

latent variables that caused the cost (e.g., increased caution). However, because the models do

not predict PM performance, they do not reveal to what degree cost-related mechanisms underlie

PM performance. For example, it is not clear to what degree the delay mechanisms underlying

cost (increased OT thresholds) actually facilitate PM. Recently, Anderson et al. (2018) aimed to

investigate this using a between-subjects experiment with multiple PM conditions, including

'standard' conditions that added a typical PM task to the OT, 'boundary' conditions that

instructed participants to increase their OT caution but *not* to monitor for PM items, and

'monitoring' conditions that instructed participants to check for PM items every trial. They found

that 'boundary' PM conditions increased OT thresholds and yet produced similar PM accuracy to

'standard' conditions (and lower than 'monitoring' conditions). They argued that this indicated

OT thresholds did not benefit PM. However, it may be that OT caution did benefit PM, but that

benefit was offset by another PM process. The boundary condition explicitly instructed

participants not to monitor for PM items because the PM intention would automatically 'pop into

mind'. Assuming that PM decisions, like OT decisions, require evidence accumulation, this

instruction may have discouraged maintaining a low PM threshold, reduced the capacity devoted

to PM, or reduced any inhibition of OT processing that may occur in response to PM trials. Even

if the reviewed experiment had not explicitly discouraged PM monitoring, participants might

take the emphasis on OT caution to imply that PM is relatively unimportant, leading to similar

confounds. We believe the best way to transcend such limitations is to model PM processes directly, allowing estimates of a range of well specified processes that contribute to PM performance. We have recently introduced such a model (Strickland, Loft, Remington, & Heathcote, 2018), termed *Prospective Memory Decision Control* (PMDC). The next section introduces PMDC, and describes our recently published work fitting the model to PM data sets.

Racing to Remember: A Full Model of Event-Based Prospective Memory

In contrast to the DDM, which can only accommodate two responses with its' standard architecture, the LBA can easily accommodate both multiple choice OT responses and the PM response without sacrificing mathematical tractability. Thus, PMDC specifies an LBA race to threshold between the OT decision and the PM process. We depict PMDC, as it would apply to a binary-choice lexical decision task with an additional PM requirement, in Figure 2. There are two aims in fitting PMDC to observed data. The first is to evaluate whether the model can account for actual human performance. To test this, we ran two long experiments (almost 4000 trials per participant) so that we could observe a reasonable number of PM trials per participant per PM condition (84) (Strickland et al., 2018). Both experiments included lexical decision tasks with an additional PM requirement. Both experiments included control conditions, and produced PM cost effects (longer non-PM trial RTs in PM blocks than control). In addition, each experiment included an influential manipulation of PM accuracy taken from previous PM literature. Below we describe each experiment, as well as the ability of PMDC to fit the data from each.
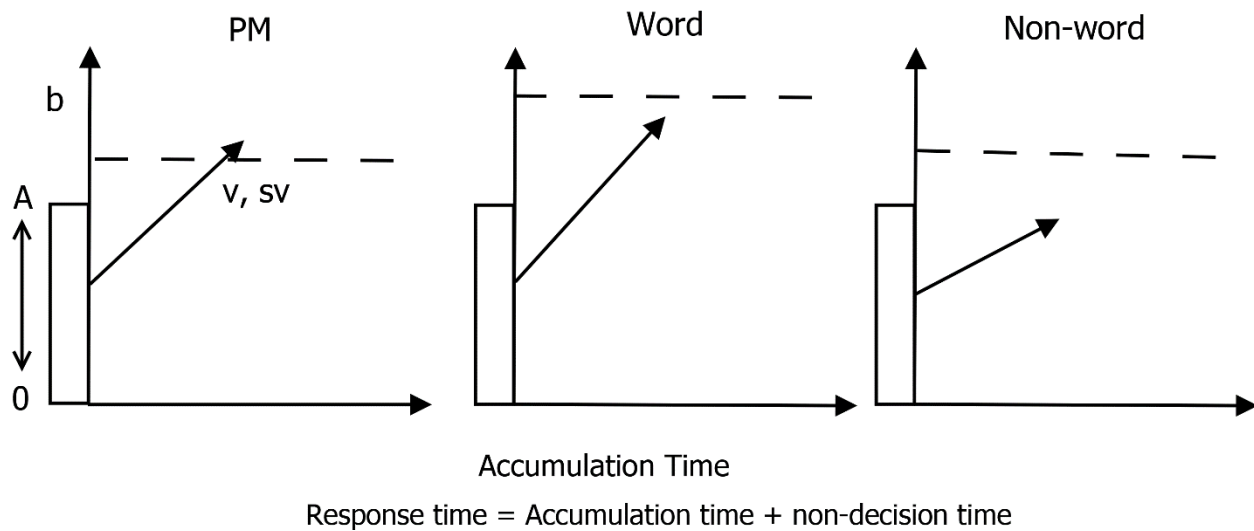
Response time = Accumulation time + non-decision time

Figure [6 – 2]. The PMDC model, as it would apply to a lexical decision task with additional

PM requirements. The model includes a three accumulator LBA race to threshold (Brown &

Heathcote, 2008). PM hits occur when the PM accumulator is the first to reach threshold on PM

trials. PM errors occur when the ongoing task accumulators hit threshold before the PM

accumulator on PM trials.

The first experiment manipulated PM *focality*, which is the degree to which ongoing task

processing enables processing of PM target features (Einstein et al., 2005; McDaniel & Einstein,

2000). The within-subjects design included control conditions, a focal PM condition (make PM

responses whenever you see a single target word), and a non-focal PM condition (make PM

responses to any word within a target category, e.g., any word that is an animal). The experiment

replicated previous studies (e.g., Einstein et al., 2005; Loft & Remington, 2013) in finding high

PM accuracy with minimal PM cost for the focal PM task, and lower PM accuracy with more

substantial cost for the non-focal PM task. We found that PMDC could fit the observed data, in

terms of both RT distributions and accuracy. This included the non-focal PM cost effect, as well as the effects of PM focality on PM accuracy and PM cost.

The second experiment manipulated the perceived importance of the PM task, including control conditions, a condition where the importance of the PM task was emphasized (important PM), and a condition where the importance of the ongoing task was emphasized (unimportant PM). For both PM conditions, the PM task was to respond to any letter strings containing a target syllable (e.g., 'tor'). Whereas the PM task in the first experiment was stimulus-specific (PM items were always words), the PM task in the second experiment was not (PM items could be words and non-words). We replicated previous studies (e.g., Ball & Aschenbrenner, 2017; Horn & Bayen, 2015; Kliegel et al., 2004) in finding higher PM accuracy and also higher PM cost when PM was important. As with the first experiment, we found that the PMDC architecture provided good fits to observed performance. This included the PM cost effect, as well as the effects of PM importance on PM accuracy and on PM cost.

Given adequate fit to a data set, the subsequent aim of fitting PMDC is to ascertain the latent psychological mechanisms underlying the data. For example, PMDC measures the degree of *capacity sharing* between PM tasks and ongoing task processing. Following recent PM literature (Bugg, McDaniel, & Einstein, 2013), PMDC also incorporates *cognitive control*, the processes that allow humans to deviate from routine behavior and act in a goal-directed manner. Drawing on the dual mechanisms framework of cognitive control (Braver, 2012), PMDC includes *proactive control* and *reactive control*. Below we discuss these capacity and control processes in more detail, as well as the evidence for each provided by the reviewed experiments.

Model Mechanisms

Capacity Sharing

PMDC tests for capacity sharing by comparing non-PM trial accumulation rates across PM conditions and control conditions, similar to previous modeling of the OT. PMDC replicated previous models by indicating that non-PM accumulation rates did not differ across PM blocks and control blocks, suggesting no capacity sharing between PM monitoring and the ongoing task. This included a condition in which the importance of the PM task was emphasized, where it has been argued that participants shunt additional resources away from the OT and towards PM (McDaniel & Einstein, 2000). In addition to OT capacity, PMDC includes a measure of PM capacity (the PM accumulation rate). As PM targets were matched across important and unimportant PM conditions, differences in PM accumulation rates would point to differences in PM capacity. However, we found that PM importance did not affect the PM rate, indicating the importance emphasis did not increase the capacity allocated to PM monitoring.

Proactive Control

Proactive control refers to processes that act in advance of a target event, in order to prepare the cognitive system for when that event occurs (Braver, 2012). Although this could potentially include control over attention and cognitive capacity, it appeared not to in the previous OT modeling, given the lack of evidence for capacity sharing. Thus, PMDC includes proactive control in terms of increases in OT thresholds so that OT decisions do not pre-empt PM processes, in line with the delay theory of PM cost. In both experiments, PMDC replicated previous OT modeling in demonstrating support for this mechanism (larger OT thresholds in PM blocks). In addition, the smaller cost in focal conditions than non-focal owed to smaller increases

in OT thresholds, and the larger cost in important conditions than unimportant owed to large

increases in OT thresholds.

In addition to proactive control over OT decisions, PMDC includes another form of

proactive control – control over the PM threshold. Decreasing the PM threshold increases the

probability that the PM response will reach threshold before the OT response, improving PM

accuracy. In line with this, we found lower PM thresholds when the importance of PM was

emphasized as compared with when the ongoing task was emphasized. Interestingly, the model

indicated that adjustments to PM thresholds were much more critical to PM accuracy than

adjustments to OT thresholds. This could explain Anderson, Rummel and McDaniel's (2018)

finding that emphasizing OT caution, but discouraging PM, did not improve PM. Standard PM

conditions, or PM conditions that encourage monitoring may encourage maintaining a low PM

threshold, whereas conditions that de-emphasize PM may not.

Reactive Control

Reactive excitation. Reactive control processes are those that occur at the time of a

target event, in order to facilitate the appropriate response to that event (Braver, 2012). In terms

of PM, this refers to the processes activated by the stimulus on PM trials that facilitate PM

responding. As thresholds are assumed to be set prior to the start of each trial, reactive control

affects accumulation rates. Figure 3 displays how rates can be controlled under PMDC. The

processing of PM inputs activates a PM detector, which then provides evidence to the PM

accumulator (pathway A1). In line with this, in both experiments in Strickland et al. (2018) we

found that PM accumulation on PM trials was greater than on non-PM trials. More interestingly,

we found faster PM accumulation for focal PM than non-focal PM. This may owe to greater

activation of the PM detector for focal PM compared to non-focal PM. PM activation may be

greater for single-target focal PM because the mapping between the target and the PM rule is more direct (is the presented word the PM target word) than the mapping between categorical non-focal targets and PM (does the presented word belong to a category that is the PM target category).
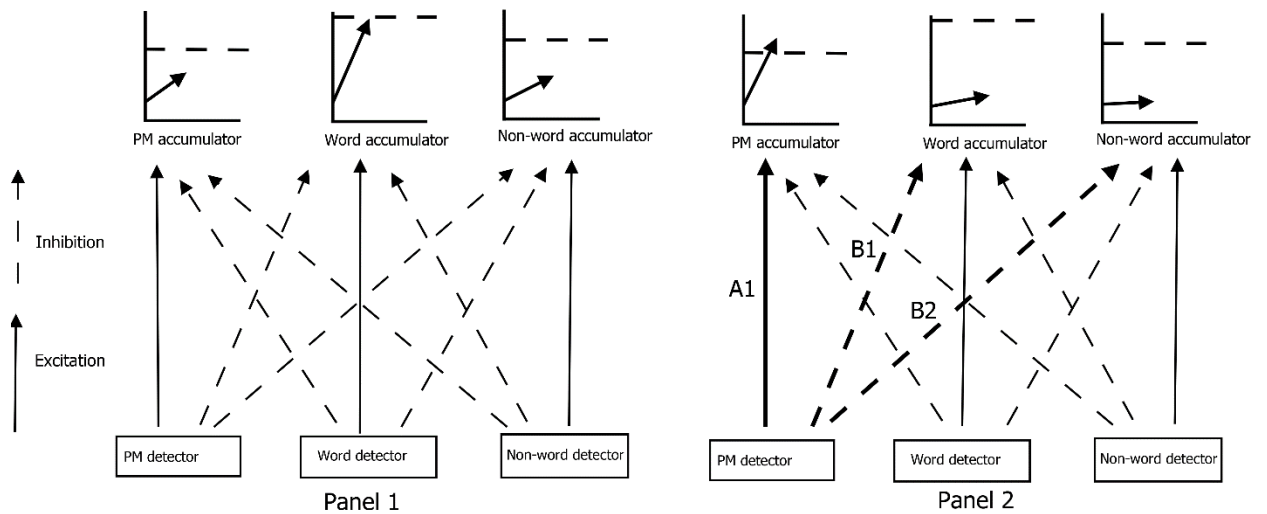

Figure [6 – 3]. Reactive control under PMDC, as it applies to a lexical decision task with an additional PM demand. During encoding, detectors for each decision are activated by stimulus features: `word', `non-word', and `PM'. This activation increases accumulation to the corresponding decision (e.g., PM inputs increase PM accumulation speed via pathway A1), referred to as excitation. Activation also inhibits accumulation towards competing decisions (e.g., PM inputs decrease ongoing task accumulation speed via pathways B1 and B2).

Reactive inhibition. PMDC also proposes that on PM trials, PM inputs can inhibit the ongoing task accumulators, slowing accumulation speed. This could explain why OT RTs are slower to non-PM items that include substantial PM-related input, but do not actually require a

PM response, often referred to as PM 'lures' (Knight et al., 2011; Scullin, Einstein, & McDaniel, 2009; Scullin, McDaniel, & Einstein, 2010). An earlier simulation model of PM (Gilbert, Hadjipavlou, & Raoelison, 2013) also included inhibition between PM and OT processes. However, the complexity of this model's architecture did not allow quantitative fits to each individual's data. To allow comprehensive fits to each participants' data, PMDC instantiates inhibition in a 'feedforward' manner. With feedforward interactions, PM inputs can inhibit OT accumulation, but this inhibition is independent of the evidence already accumulated to each decision. This permits retaining the assumption that accumulation rates are independent, which in turn supports an analytic likelihood while still capturing possible interactions between accumulators (Brown, Marley, Donkin, & Heathcote, 2008; Trueblood, Brown, & Heathcote, 2014). Fitting models with more complex competition between accumulators, such as the 'Leaky Competing Accumulator' (Usher & McClelland, 2001) is challenging, because they tend not to provide analytic likelihoods, greatly reducing computational speed. Furthermore, more complex model mechanisms can trade-off with each other, making it difficult to identify model parameters (Miletić, Turner, Forstmann, & van Maanen, 2017).

Reactive inhibition can be measured by comparing accumulation to OT decisions on PM trials with accumulation to OT decisions on non-PM trials[1]. In both reviewed experiments to which we fitted PMDC, we found strong evidence of reactive inhibition over OT accumulation on PM trials. Furthermore, our model indicated that reactive inhibition was more critical to PM accuracy than proactive control over the OT, and was the strongest correlate with PM accuracy

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[1] This requires that PM and non-PM stimuli be similar in terms of the evidence they provide for ongoing task decisions. In our experiments, we took measures to assure this was the case. We matched word PM stimuli to ongoing task stimuli in terms of word length and written word frequency. We matched non-word PM stimuli to ongoing task stimuli in terms of length and sub-syllabic transition frequencies.

across participants. We also found that variations in reactive inhibition were critical to the effects of PM focality and importance. We found greater inhibition to focal PM targets than non-focal PM targets. As we also found an increase in PM accumulation rate to focal PM targets, this increased inhibition may owe to stronger PM inputs. With important PM, we found greater inhibition than unimportant PM, with no difference in PM excitation. This suggests that although inhibition 'reads-out' reactively, in that it only occurs on PM trials and not non-PM trials, reactive control settings may be subject to strategic control. For example, when PM is important participants may inhibit ongoing task decisions more for the same amount of PM related input.

Future Directions

This chapter reviewed evidence accumulation modeling in PM research, focusing on the PMDC model, a computational model that can account for the entire array of data from the Einstein & McDaniel (1990) paradigm. Although PMDC corroborated the findings of previous OT modeling, it revealed additional mechanisms that were critical to PM accuracy, such as reactive inhibition of OT processes on PM trials and control over PM thresholds. To date, PMDC fits have only been published for the two Strickland et al. (2018) experiments, and thus there is potentially much more to be learned from further applying the PMDC model. In the next section, we discuss future applications of PMDC, including our ongoing work. Interested readers should note that although our initial fits required many data points per participant, this requirement may be relaxed for future investigations with the incorporation of prior information into modeling, or with a hierarchical model that pools information across many participants.

Future Paradigms

Generalizing to more PM paradigms. It would be worth examining how the PMDC model generalizes to a broad range of PM paradigms. For example, in the reviewed studies that

tested PMDC, one PM target was presented for every 14 non-PM items, which is a relatively high PM frequency. Ideally, we would like to generalize PMDC to much lower PM frequencies (e.g., 1:100). Thus, our ongoing work investigates the effect of PM target frequency on PMDC's parameters. Of course, low PM frequency paradigms observe fewer PM trials per participant than high frequency paradigms, and this makes modeling each individuals' data challenging.

In the reviewed studies, we employed a 'PM instead' instruction, in which participants were required to submit PM responses instead of OT responses on PM trials. This is similar to a common PM paradigm in the literature, which instructs participants to make a PM response when the target is presented (e.g., Einstein et al., 2005; Loft & Humphreys, 2012; Loft & Remington, 2013; Scullin, McDaniel, & Einstein, 2010; Smith, 2003). However, some PM paradigms require participants to submit their PM response after their OT response (e.g., Loft et al., 2008; Marsh et al., 2003) . It would be interesting to investigate how such a PM response mode affects PMDC. We have already modeled PM cost in this 'PM after' paradigm (Heathcote et al., 2015), and found the same underlying latent variables as the 'PM instead' paradigm (proactive control over thresholds with no capacity sharing). However, we have not yet modeled PM RTs and accuracies from such a paradigm. It would be difficult to do so, because the motor production time for the initial OT response is not directly identifiable, and so it confounds the measurement of the subsequent PM RT. Instead in our ongoing work we are investigating a modified lexical decision task which requires participants perform both their PM and OT decisions on every trial, but submit one response which encompasses both (possible responses are non-PM word, non-PM non-word, PM word, PM non-word).

Generalizing to human factors environments. Given that PM is required in many safety critical work settings, it is important to apply PMDC to understand performance in such

tasks. In our ongoing work, we have applied PMDC to understand performance of simulations of

Air Traffic Control and Maritime Surveillance. In these environments, we find similar hallmarks

of proactive and reactive control as in basic PM paradigms. However, in contrast to the basic

paradigms, in these applied simulations we *do* find some evidence of capacity sharing between

PM monitoring and ongoing tasks. This may occur because the applied ongoing tasks demand all

available cognitive capacity, taking performance to the 'red zone' (Hart & Wickens, 2010), such

that any additional capacity required by PM monitoring must be sacrificed from the ongoing

task. In contrast, in the basic paradigms, participants may not need to fully engage their capacity

to perform ongoing task decisions, leaving capacity idle to be recruited for PM monitoring under

PM conditions, consistent with subjective reports of reduced mind wandering with PM (Rummel,

Smeekens, & Kane, 2017). Thus, to determine whether PM and ongoing tasks share capacity in

applied settings of interest, it appears PM must be studied in environments with representative

capacity demands.

   Applying PMDC to examine individual differences, abilities in other tasks, and

neural substrates. In line with PMDC's emphasis on cognitive control, a recent large scale

individual differences study has revealed a relationship between PM performance and cognitive

control ability (Ball & Brewer, 2017). This work also examined PM cost with ex-Gaussian

descriptive modeling of RTs. Ideally, future work could pair the benefits of PMDC – a full

process model- with such an individual differences approach, in order to examine how ability in

other cognitive control tasks corresponds to PMDC mechanisms. PMDC was fitted with

Bayesian methods, which makes it easy to explore relations between covariates and parameter

values with plausible value correlations (Ly et al., 2018). It would also be worthwhile to explore

the neural bases of PMDC's parameters with such correlations. Furthermore, trial-by-trial level

neural measurements might also be included in the model to constrain parameter estimates, known as 'joint modeling' (Forstmann & Wagenmakers, 2015).

Future Models

Future work may also extend the PMDC model. Currently, the architecture only predicts PM errors when the PM accumulator loses the race to decision threshold against one of the ongoing task accumulators. Although this assumption was adequate to account for the benchmark PM data we collected, it might not be in other paradigms. For example, the Dynamic Multiprocess View (Scullin, McDaniel, & Shelton, 2013) proposes that monitoring may fail entirely when PM events are very rare. Such monitoring failures would lead to PM errors where no evidence at all enters the PM accumulator, rather than the PM accumulator losing the race to threshold. Similarly, under high retrospective memory demands (e.g., a PM task where participants must respond to a list of many targets), participants may forget that items are PM targets, leading to no PM evidence accruing at all to those targets. Due to the LBA's assumption of independence between accumulators, including such failures in the architecture is straightforward, and failure rates can be reliably measured (Matzke, Love, & Heathcote, 2017). We are currently searching for data suitable to identify failures of the PM decision to accumulate.

Another extension of PMDC would be to include a serial PM 'target-check' mechanism, in line with the suggestions of other authors that increased DDM non-decision time under PM conditions indicates serial checking (e.g., Horn & Bayen, 2015). Given the DDM non-decision time effects are small, the check would likely occur only on a small proportion of trials. However, given PM accuracy is often reasonably good, the parallel PM accumulator would also likely account for some PM accuracy, leading to a model that included a mixture of serial and

parallel PM processes. Adding the serial component to PMDC would prevent writing out an analytic likelihood, greatly impeding fitting. However, recent advances in Bayesian estimation using probability density approximation methods (Turner & Sederberg, 2014) promise tractable model fitting without analytic likelihoods, which may enable a serial model.

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