Original Article

Analyzing Response Time Distributions

Methodological and Theoretical Suggestions for Prospective Memory Researchers

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Abstract. The analysis of response times from prospective memory experiments has resulted in multiple theoretical propositions about the role of attention in prospective memory. Extant theories of prospective memory are in good agreement that attention is necessary for detecting intention-related cues. However, these theories were primarily formulated to describe differences in mean reaction times across experimental conditions. While this approach has been fruitful for establishing a fundamental relation between attention and prospective memory, reaction time modeling techniques can be applied to prospective memory data to better constrain theorizing. In the current work, the ex-Gaussian distribution is fit to data from a prospective memory task. The results from this analysis suggest that modeling reaction time data has the potential for clarifying our understanding of the role of attention in prospective memory.

Keywords: prospective memory, response time distribution, modeling, ex-Gaussian

Prospective memory is used whenever people delay their behavior until a future cue, time, activity, or context signals that it is appropriate to complete their intention. Attention can play a role in the ways that intentions are formulated, intention-related information is detected, and planned actions are retrieved from memory. However, researchers have only recently begun to specify the attentional components of fulfilling intentions for the future (Guynn, 2003; Marsh, Hicks, & Cook, 2005; McDaniel & Einstein, 2000; Smith, 2003). At this point there is general agreement that attentional mechanisms support prospective memory abilities under many conditions. Unfortunately, theorizing on this topic has primarily relied upon measures of central tendency to assess attentional demands. The analysis of response time (RT) distributions has a rich history in the psychological literature (Luce, 1986) and can be profitably incorporated to help promote deeper theorizing about the relation between attention and prospective memory.

Most research investigating attentional demands in prospective memory has been derived from tasks that follow from a basic setup. In these studies, participants are instructed to complete a two-alternative forced choice task as quickly and accurately as possible (i.e., simple decision making). At the outset of a typical prospective memory experiment, participants receive the additional instructions that some special event may occur in the context of the ongoing task that they will be performing later in the experiment. Participants are instructed to make a special response if and when this event occurs. In these cases, the special event is the prospective memory cue and the question typically addressed in these speeded response paradigms is whether or not there was additional attention employed to detect the cues. If there is a difference in the average RT to classify non-cue stimuli when the participants possess the intention relative to when they do not possess the intention, referred to as task interference or cost to the ongoing task, then prospective memory researchers have inferred that attention was used to support completing the intention. These costs are typically observed as differences in average RT to some ongoing task (i.e., task interference; Hicks, Marsh, & Cook, 2005) but costs are sometimes exhibited in reductions in ongoing task accuracy. In the current work I will be predominantly concerned with event-based prospective memory but later in the manuscript I will speculate on modeling RT distributions from time- and activity-based prospective memory tasks.

At a theoretical level of analysis there have been several proposals about the processes that contribute to the cost of possessing an intention. One idea is that people are allocating some degree of attention toward searching for intention-related information in the context of an ongoing task (Einstein & McDaniel, 2008; Marsh et al., 2005). However, the recruitment of attentional processes need not be a conscious strategy that is exerted on every single trial of an ongoing task (for a discussion of this issue see Knight, Ethridge, Marsh, & Clementz, 2010; Smith, Hunt, McVay, & McConnell, 2007). Importantly, the demands on attention for successfully carrying out prospective memories are most likely multifaceted, with the various facets jointly contributing to detecting cues. The question posed in the current work is whether or not these components of monitoring con-

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tribute differentially to RT distributions that are typically found in prospective memory tasks.

Extant theories, such as the two-process model of strategic monitoring (Guynn, 2003), the attention allocation theory (Hicks et al., 2005), the preparatory attention and memory theory (Smith, 2003), and the multiprocess view (McDaniel & Einstein, 2000), differ in their interpretations of the cost; however, these theories are neither mutually exclusive nor exhaustive explanations for the source of task interference (Hicks et al., 2005). These theories agree that attention is necessary for successfully fulfilling prospective memories, but debate exists over how well task interference tracks various attentional processes (Einstein & McDaniel, 2010; Smith, 2010). One approach to investigating the attentional mechanisms underlying task interference is to analyze RT distributions rather than relying solely on measures of central tendency.

For example, West, Murphy, Armilio, Craik, and Stuss (2002) explored cognitive control by investigating RT distributions in younger and older adults who completed a series of four *n*-back tasks that differed with respect to the presence of distracting information and with respect to whether the response classified the immediate stimulus or the stimulus on the previous trial (i.e., 1 back). Performance variability, as assessed by fitting an ex-Gaussian distribution to the response latencies, was increased when cognitive control was needed for successful task performance. Also, older adults exhibited an increase in the positive skew of their response latency distributions, which was taken as evidence that they suffered periodic lapses of intention due to variation in executive functioning. West et al.'s results demonstrate that an investigation of RT distributions allows researchers to develop deeper theories about performance in a task rather than relying solely on measures of central tendency. To the degree that executive functioning is important for detecting prospective memory cues (Brewer, Knight, Unsworth, & Marsh, 2010; Smith & Bayen, 2005), investigating various components of the RT distribution may prove useful for arbitrating between theoretical propositions for the role of attention in prospective memory.

RT Analysis

In this study, the RTs from a lexical decision task will first be analyzed using the standard approach for prospective memory studies, followed by discussion of the ex-Gaussian analysis for estimating separate components of the RT distribution (Hohle, 1965; Luce, 1986). Additional methodologies for analyzing RT distributions are available, however, the focus of the current review is to highlight a quick and easy technique for separating the RT distribution into multiple components. Perhaps most importantly, researchers who are interested in analyzing RT distributions can implement this technique with simple and relatively easy-to-use computer software.

The Standard Practice for Deriving Mean RT

When using the lexical decision ongoing task, the event-based cues in this type of paradigm are often words and so the decision was made early on to analyze only word trials from the lexical decision task because interference to word and nonword trials varies as a direct function of whether the cues are words or nonwords (Cohen, Jaudas, & Gollwitzer, 2008a). After restricting the analysis to word trials, the first step in analyzing lexical decision task data has been to conduct an analysis of accuracy in identifying a word as a word. This step is important for two reasons. First, ongoiong task accuracy may be a supplemental measure of task interference (Smith & Bayen, 2004). Second, erroneous word decision trials should not contribute to the analysis of lexical decision RTs because they are derived from a different distribution of latencies (i.e., errors typically exhibit slower response latencies). Following the elimination of erroneous trials from the set of word trials, the next step is to exclude event-based cue trials and potentially to exclude several trials following the cues (e.g., Cohen, Jaudas, & Gollwitzer, 2008b). The final step before aggregating the data to the participant level is to identify word trials within each participant's response set that are faster or slower than 2.5 *SD*s of that participant's mean accurate word identification RT (Ratcliff, 1993). Importantly, decision latencies should also be examined within a condition and also within a block of trials using these same criteria to avoid contaminating the dependent measure (for a discussion of these issues see Smith, 2010). Once these trials are identified they are replaced by missing values so they do not contribute to a participant's mean RT.

After the previous steps have been completed, the trial-level data are aggregated to the participant level of analysis by calculating the mean RT for each participant. Similar to the analysis of outlying responses described previously, another consideration of participants *within a condition* who fall below or above 2.5 *SD*s of that groups mean is in order. After removing these participants from the RT analysis (and noting whether their removal qualitatively influences the results), researchers can investigate the descriptive statistics in each condition and look for differences across conditions using traditional statistical methodology.

Clearly, the traditional approach to analyzing mean RTs from a prospective memory paradigm has both benefits and drawbacks. The primary benefit seems to be that the level of sophistication needed to derive and analyze mean RT is not particularly high. Another benefit to analyzing mean RT is that the measure summarizes a great deal of information in one summary statistic. Investigating mean RT has been very useful in the development of theories of prospective memory, but it does have limitations. Perhaps the biggest drawback to reducing RT data to one dependent measure in the standard analysis is that an egregious amount of data is lost from consideration. Another drawback to analyzing mean RT is the inherent bias from larger or more extreme values. Interpretive problems can arise when using measures of central tendency to describe data that is positively skewed or not normal as is typically the case with RT distributions. Most RT distributions are skewed by slower responses and two questions emerge for prospective memory researchers. Should we be concerned with the skew, and if so, how should we deal with the skew? Although related, these questions address fundamentally different issues. The former essentially asks whether or not having an intention should result in slower ongoing task latencies for some proportion of the trials. This is very much a theoretical proposition and one that has been made by Guynn (2003) among other researchers (Braver, Gray, & Burgess, 2007; Marsh et al., 2005; West et al., 2002), but remains elusive when investigating only mean RT. The answer to the latter question depends on whether the skew of the RT distribution is functionally related to possessing an intention. Using the ex-Gaussian analysis presented in the subsequent section will allow researchers to isolate multiple components of the RT distribution for further empirical and theoretical analysis.

Modeling RT Distributions: The Ex-Gaussian Function

An alternative technique for analyzing RTs is to assume and subsequently fit a statistical distribution that may have generated the RTs. This approach has been used successfully to describe RT distributions from a wide range of cognitive tasks including Stroop (Heathcote, Popiel, & Mewhort, 1991), Recognition Memory (Ratcliff & Murdock, 1976), Free Recall (Wixted & Rohrer, 1993), and Lexical Decision (Yap, Balota, Cortese, & Watson, 2006). One of the most commonly assumed distributions for modeling RT data in mainstream cognitive psychology is the convolution of the Gaussian and Exponential distributions (the ex-Gaussian distribution; Hohle, 1965; Luce, 1986). In the present article I will focus solely on the ex-Gaussian distribution. However, other probability distributions have been successfully fit to RT distributions including the Gumbel, Wald, Lognormal, and Weibull. Please note that any analysis of RT distributions should investigate a variety of a priori assumptions about the underlying probability distribution that generated the data (Cousineau, Brown, & Heathcote, 2004). The ex-Gaussian distribution was chosen as an exemplary case for demonstration purposes and because it provides a reasonable fit to RT data under broad sets of conditions (Luce, 1986). Early on, researchers suggested that descriptions of the distribution's shape (parameter estimates) could lead to strong inferences about the underlying mechanisms (cognitive processes) that educed certain patterns of responding (Hohle, 1965; McGill, 1963). This position has generated considerable criticism because the mapping between parameter estimates and cognitive processes has been tenuous (Matzke & Wagenmakers, 2009). Regardless, the ex-Gaussian distribution fits the typical RT data quite well (Heathcote et al., 1991; Luce, 1986).

The convolution of the Gaussian and Exponential distributions assumes that the two reflect independent contributions to the overall statistical distribution. As can be seen in Equation 1, at each time point x, the ex-Gaussian distribution is described by the mean (μ) and variance (σ) of the Gaussian distribution and the mean (τ) of the exponential distribution (note that τ is both the mean and standard deviation of the exponential distribution; see Wixted & Rohrer, 1993 for full derivation of the ex-Gaussian distribution).

$$f(x|\mu,\sigma,\tau) = \frac{1}{\tau\sqrt{2\pi}} \exp\left(\frac{\sigma^2}{2\tau^2} - \frac{x-\mu}{\tau}\right) \cdot \int_{-\infty}^{\left[\left(\frac{x-\mu}{\sigma}\right)-\left(\frac{\sigma}{\tau}\right)\right]} \exp\left(-\frac{y^2}{2}\right) \mathrm{dy} \qquad (1)$$

Ratcliff (1978) used the method of moments to demonstrate that the mean (Equation 2) and variance (Equation 3) of an empirical RT distribution can be expressed as functions of the ex-Gaussian parameters.

$$E(x) = \mu + \tau \qquad (2)$$

$$Var(x) = \sigma^2 + \tau^2 \qquad (3)$$

To obtain parameter estimates from the ex-Gaussian distribution, the parameter space is explored in a search for the values of the three parameters that maximize the likelihood of producing the data (Cousineau et al., 2004; Myung, 2003). There are a variety of likelihood estimation techniques and a full description of model fitting procedures is beyond the scope of this article. However, many excellent treatments exist (for a description see Heathcote et al., 1991). Fortunately, the computational workload that is needed for the maximum likelihood estimation techniques has been dramatically reduced and researchers can easily obtain parameter estimates using freely available software (e.g., Quantile Maximum Probability Estimation, QMPE; Brown & Heathcote, 2003; Cousineau et al., 2004).[1] In most cases, QMPE provides robust fits to RT distributions containing at least 40 trials of a given trial type.

Examples of ex-Gaussian distributions can be found in Figure 1. As can be seen in Figure 1a, increases in μ lead to distributional shifting to the right. Whereas in Figure 1b, increases in τ lead to distributional skewing. Together, the mean of the Gaussian component describes the location of the leading edge of the distribution of RTs and the mean of the Exponential component describes the degree of skew in the RT. These components may be affected differently by various manipulations. For example, certain types of prospective memories may create differences in τ when compared with control conditions whereas other types of intentions may create differences in μ, τ, or both. Analogous to the standard approach described earlier, researchers can choose to use the ex-Gaussian approach to analyze RT distributions by trial type (e.g., only correct word trials vs. only correct nonword trials). And, as with the standard analysis of RT data, prospective memory cue trials should be excluded. Another interesting direction is to model RT distributions for

[1] http://www.newcl.org/software/qmpe.htm

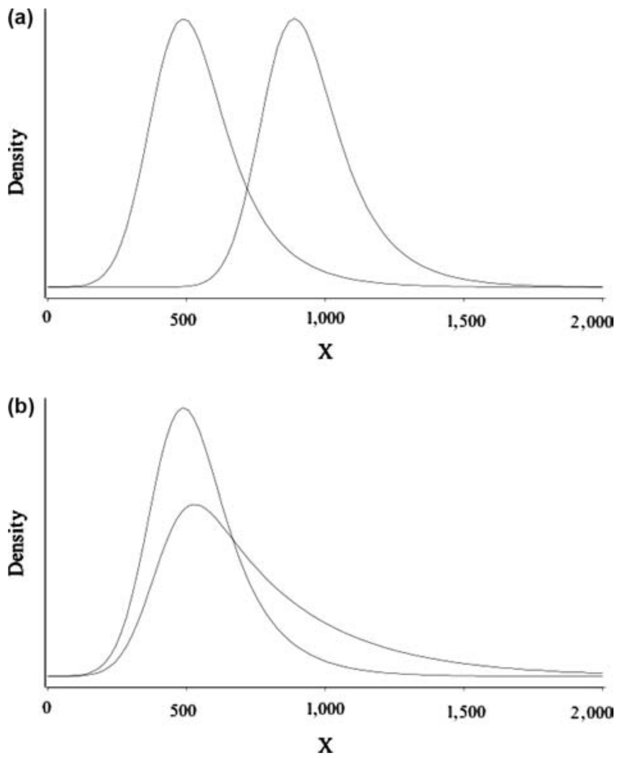

Figure 1. (a) Two hypothetical ex-Gaussian distributions with only changes in μ. (b) Two hypothetical ex-Gaussian distributions with only changes in τ.

both correct and erroneous trials separately to assess important differences in processing non-cue trials provided that there are enough trials in each case.

The Current Study

To demonstrate an analysis of task interference in prospective memory using the entire RT distribution, I provide data from a standard event-based prospective memory experiment. In this task, participants completed a series of lexical decisions while possessing an intention to make a special response to words that contained the syllable TOR (Einstein et al., 2005). This syllable intention has been used regularly in different laboratories to investigate prospective memory costs to ongoing activities (e.g., Brewer et al., in press; Einstein et al., 2005).

Method

Participants

University of Georgia undergraduates volunteered in exchange for partial credit toward a research appreciation requirement. Fifty-three participants completed a prospective memory task and all participants detected at least one cue. Data from both a lexical decision baseline condition and an event-based prospective memory condition will be presented.

Materials and Procedure

The baseline ongoing lexical decision task consisted of 105 trials, with equal numbers of valid English words and pronounceable nonwords that were randomly presented on a computer monitor (for a complete description of the lexical decision task procedure see Marsh, Hicks, & Watson, 2002). The 52 valid words were selected from the Kucera and Francis (1967) normative compendium. Upon stimulus presentation, participants were instructed to press the word key with their right index finger or the nonword key with their left index finger as quickly as possible. Participants were instructed that they were going to be taking part in an experiment with multiple phases and that they would receive instructions for each phase before beginning that part of the experiment. In the first phase of the experiment, participants decided whether strings of letters were valid English words or not (i.e., Lexical Decision Task). Following the lexical decision instructions, all participants were presented with 105 letter strings of which 52 were valid English words and 53 were pronounceable nonwords. All words and nonwords were presented in uppercase and one at a time in the center of the screen. Participants were allowed to make their response by pressing one of the two keys on the keyboard (F for nonword and J for word). After making each response, participants were presented with a "waiting" message at which point they pressed the spacebar to initiate the next lexical decision trial.

After completing the baseline lexical decision task, participants were told that we were interested in their ability to remember to perform an action in the future. Then, participants were given an event-based intention to make a special key press ("/") during the waiting message after responding to any word with the syllable "TOR" in it (Einstein et al., 2005). The syllable TOR only occurred on word trials in the lexical decision task (e.g., DOCTOR, FACTOR, PASTOR, and TRACTOR). The general parameters of the lexical decision task did not differ from the baseline condition, and the four cues always occurred on the 25th, 50th, 75th, and 100th trial. After the experimenter reiterated the instructions and was sure that the participant fully understood the requirements, a 2-min distractor task was administered after the intention was formed (i.e., embedded figures puzzle task). After the distractor task, the prospective memory task was not mentioned again.

Data Preparation and Analysis

Only the word decisions from the baseline and prospective memory conditions were examined in the following analyses to remain consistent with previous studies. Also, any RT that was outside of 2.5 *SD*s of a participant's mean was excluded from the analyses. For the standard analysis, the data were aggregated to participant's mean RT in each

Table 1. Mean accuracy, RT, variability, and parameters for the ex-Gaussian analysis (*SE* in parentheses)

Standard analysis			Ex-Gaussian		
Condition	Accuracy	*M* RT	μ	σ	τ
Baseline	.96 (.004)	782.55 (19.52)	561.00 (19.71)	45.11 (5.14)	220.98 (9.99)
Intention	.95 (.004)	823.02 (16.91)	568.30 (13.75)	52.31 (6.89)	251.93 (8.90)

condition corresponding to the description of analyzing prospective memory data provided earlier. For the ex-Gaussian Analysis, each participant's raw data were fed into the QMPE program provided by Heathcote and colleagues (2004). Estimates of μ, σ, and τ were derived for each participant separately in order to localize differences in RT distributions between conditions. A fixed number of quantiles (0, .2, .4, .6, .8, 1) were used in the estimation procedure for each participant's RT in milliseconds. Model fits to all participants were successful and converged within 300 iterations.

Results

As mentioned earlier, all participants detected at least one event-based prospective memory cue. Cue detection was slightly higher than that reported in previous studies ($M = 74\%$, $SE = .04$). Table 1 contains means and standard errors for all of the following analyses of RTs from this paradigm.

Standard Analysis

As can be seen in Table 1, and replicating much previous research, there was a significant difference in RTs between the baseline and prospective memory conditions, $t(52) = 2.73$, $p < .01$, $d = .39$. These results are consistent with the notion that participants recruited attention to monitor for prospective memory cues and that this additional allocation of attention resulted in a significant amount of task interference. However, there were no differences in lexical decision accuracy for word trials, $t < 1$, ns. Furthermore, there was a marginal correlation between cue detection and task interference in the prospective memory condition, $r(52) = .24$, $p < .09$. The relation between cue detection and task interference has not been consistently demonstrated in various prospective memory studies (Hicks et al., 2005). However, several reasons may exist for the lack of a consistent correlation including poor reliability of prospective memory measure, small sample sizes, and ceiling effects. Regardless, the correlational analysis in this study is indicative of a positive relation between the time participants were taking to make lexical judgments and the proportion of cues they detected.

Ex-Gaussian Analysis

Table 1 contains the ex-Gaussian parameter estimates derived from the QMPE software provided by Heathcote and colleagues (2004) for both the baseline and prospective memory conditions. The three parameters of the ex-Gaussian distribution describe the mean location (μ) and spread (σ) of the Gaussian component and the tail (τ) of the exponential distribution. There was no significant difference in either of the Gaussian parameters μ or σ, both *t*'s < 1, ns. However, there was a significant difference between the exponential component (τ) of the baseline and prospective memory RT distributions, $t(52) = 2.92$, $p < .01$, $d = .41$. These results indicate that possessing an intention changed the relative frequency of slow responses, the duration of slow responses contributing to the tail of the distribution, or both. Moreover, the current results suggest that only one of the three possible components underlies RT differences found using the standard analysis.[2]

Discussion

The current work intends to promote a greater level of sophistication in the analysis of RT distributions drawn from prospective memory experiments, deeper theorizing about how attention contributes to prospective memory, and new research directions for prospective memory researchers. The analysis of RT costs in prospective memory experiments has recently dominated the field (for discussions see Einstein & McDaniel, 2010; Smith, 2010). Clearly, these explorations have advanced our understanding of the role of attention in prospective memory. However, recent suggestions about the multiple ways in which attention is recruited for prospective memory demands indicate that multiple dependent measures may be necessary for fully understanding the locus of task interference. Fitting statistical distributions such as the ex-Gaussian affords researchers

[2] Although participants were instructed to make a prospective memory response to any word containing the syllable TOR, the ex-Gaussian approach was also implemented to investigate the distribution of nonword RTs. The results from this analysis paralleled those found for the word trials. That is, the mean location (μ) and spread (σ) of the nonword distribution of RTs did not differ between conditions, both *t*s < 1. However, there was a significant difference between the conditions when comparing the exponential component (τ) of the nonword distributions, $t(52) = 2.70$, $p < .01$, $d = .37$.

with an atheroetical tool for decomposing the RT distribution into various components. This approach can provide prospective memory researchers with additional measurements for pushing forward theorizing about the role of attention in prospective memory.

In the current study, the results from the standard analysis are in good agreement with previous demonstrations of task interference. When participants possessed an intention to respond to words that contained the syllable TOR in a lexical decision task, their average RT on word trials was significantly slower than a baseline condition where no intention was present (see also Einstein et al., 2005). This difference in mean RT, and those previously reported in the literature, could be due to any number of factors that have bearing on the speed with which participants complete a lexical decision task. For instance, participants may actively monitor for TOR syllabi on every trial of the lexical decision task. This line or reasoning would predict a shift in the entire RT distribution drawn from an event-based prospective memory condition. Alternatively, participants may initiate transient periods of monitoring throughout the lexical decision task and these periods would be reflected in the τ parameter of the ex-Gaussian distribution (West et al., 2002). Another possibility is that a general shift in the allocation of attention from the ongoing task to the PM task would result in increase in μ and this could also be accompanied by a shift in τ if there are times when more effort is directed to the pm task either for monitoring or for making target recognition decisions. The results from the current study support the notion that momentary ruminations or monitoring about detecting TOR syllabi seem to underlie the typically observed differences in mean RT previously reported in the literature. Although suggestive, these results do *not* presently disambiguate or support any one theory of strategic monitoring. Future research should more thoroughly investigate the RT distribution from various event-based conditions to better characterize strategic monitoring and how it produces task interference.

Taken together, the results from the current analysis indicate that one component (namely τ) was responsible for mean RT differences in prospective memory tasks that embed TOR syllabi in a lexical decision task. Importantly, researchers should take great care in extrapolating these results to other types of intentions. Future research should investigate the conditions under which other components of strategic monitoring may influence the distribution of RTs drawn from prospective memory paradigms. These investigations will provide new data and novel analyses that can be used to constrain extant theories of attention and prospective memory. The ex-Gaussian model makes no assumptions about underlying cognitive processes whereas other modeling techniques (e.g., the diffusion model) make very clear and specific assumptions. The choice of a model of RT distributions should reflect the researcher's goals. If the primary goal is to characterize the RT distribution then an ex-Gaussian distribution (or any other plausible distribution) would be most useful. If the researcher's goal is to explore the underlying decision processes that change as a function of possessing an intention then a model like the diffusion model would be more useful. Horn, Bayen, and Smith (2011) report just such an analysis of prospective memory using the diffusion model.

Of course, alternative modeling techniques exist and should be examined by prospective memory researchers. Recently, interest has grown in accounting for individual differences in prospective memory abilities (Brewer et al., 2010; Einstein & McDaniel, 2008; Smith & Bayen, 2005). New modeling techniques have employed Bayesian statistical approaches to evaluate individual differences in a host of cognitive tasks including applications of the diffusion model (Lee, 2008; Lee, Fuss, & Navarro, 2006). Bayesian hierarchical models can simultaneously account for both average performance and individual variability that contribute to RT distributions (Rouder, Speckman, Sun, & Jiang, 2005). Modeling individual differences in prospective memory tasks can make great use of these Bayesian techniques. Another modeling technique that has been used to investigate attention and RT distributions is the neural accumulator modeling (Usher & McClelland, 2001). These types of models have a neurophysiological basis and can be useful for better specifying the neural components of monitoring that lead to task interference. Obviously, when a model-based analysis of RT costs is evaluated, then the researcher assumes all of the assumptions of that particular model. These assumptions about the underlying components of RT distributions are nontrivial and should be explored with great caution. Here I argue that the choice of a model of RT should be tailored to the theoretical demands that are under investigation and whether the demands be about differences between prospective memory conditions, individual differences in monitoring, or neurophysiologically-driven investigations of RT distributions. One problem with all of these models is that it is not currently clear how to incorporate event-based cue trials and prospective memory performance into a single RT model. Future work should investigate methods for characterizing not only the RT distribution and accuracy of cue trials but should also model the prospective memory cue RT distribution and accuracy all together.

The costs of possessing an event-based intention have been investigated with greater regularity then either time- or activity-based intentions (but see Hicks et al., 2005). Recently, we (Brewer et al., in press) have suggested that the division between event-, time-, and activity-based intentions reflects differences between the types of information that an individual will use to establish and complete his or her intention. More specifically, the same memory and attention system is used to complete these various intentions, but what differs is the nature of the cues that feed into the system. Following from this logic, the RT modeling techniques advocated in the current work should be useful for investigating other forms of intentions beyond event-based prospective memory. Hicks et al. (2005) discussed certain monitoring mechanisms that are necessary for successful event-based prospective memory but that may not be necessary for time-based prospective memory. Importantly, the parameters from any model can take on a variety of interpretations when there is inconsistency in the monitoring processes leading to task interference in the different prospective memory tasks.

Clearly, the preceding arguments signify a call to arms for investigating data drawn from prospective memory experiments with greater sophistication. Fortunately, the time it takes to learn these modeling techniques, to apply multiple models to any given dataset, and to interpret the results has been greatly reduced thanks to researchers in the RT modeling literature. Prospective memory researchers have already begun applying RT models to prospective memory data with interesting and informative results (Horn et al., 2011). These investigations have profitably advanced our understanding of the role of attention in prospective memory. Whereas previous theorizing about attention and prospective memory used a single dependent measure (i.e., mean RT), the approach advocated in the current work suggests that multiple dependent measures will provide greater constraints for our theoretical propositions. Future work will undoubtedly shed light on this topic and enhance our theorizing about how attention is recruited in service of fulfilling intentions.

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