A diffusion model analysis of task interference effects in prospective memory

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Abstract Holding an intention often interferes with other ongoing activities, indicating that resource-demanding processes are involved in maintaining the intention and noticing the appropriate event to fulfill it. Little is known, however, about the nature of the processes underlying this task interference effect. The goal of the present research was to decompose the processes contributing to the task interference effect by applying the diffusion model (Ratcliff, Psychological Review 85:59–108, 1978) to an event-based prospective memory task. In the first experiment, we validated the interpretation of the response criterion parameter (a) of the diffusion model as reflecting strategies to cope with the anticipated demands of a prospective memory task in the context of the ongoing task. The second experiment served to investigate which underlying processes contribute to the task interference often found with prospective memory tasks. Diffusion model analyses revealed that the task interference effect was due to (1) less efficient processing in the more demanding than in the less demanding prospective memory task and (2) a more conservative response criterion. We suggest that the anticipated demands and the additional processing demands of the prospective memory task jointly contribute to the task interference effect.

Keywords Prospective memory · Diffusion model · Task interference effect

The cognitive processes involved in remembering to perform an action in the future upon the occurrence of a certain event (e.g., giving your coworker a message when

you see them) are typically subsumed under the rubric of event-based prospective memory (PM). Unlike retrospective memory tasks, event-based PM tasks not only require the retrieval of the intended action (e.g., giving the message) but also *noticing* the event associated with the intention (i.e., seeing your coworker) and remembering that *something* needs to be done. The latter requirement is especially critical in PM tasks, because people are typically busily engaged in some other ongoing activity (e.g., writing a report) when the event occurs. This additional requirement of noticing the event and retrieving the intention has sparked considerable research aimed at disentangling the processes involved in PM performance. It has been argued that different kinds of processes, such as resource-demanding processes and rather effortless (spontaneous) processes, can contribute to the observable PM performance (cf. McDaniel & Einstein, 2000, 2007). While the group of spontaneous processes has been differentiated further—for example, in terms of discrepancy-plus-search processes and reflexive-associative retrieval processes (Breneiser & McDaniel, 2006; Guynn & McDaniel, 2007; McDaniel, Guynn, Einstein, & Breneiser, 2004; Meier, Zimmermann, & Perrig, 2006; see also McDaniel & Einstein, 2007, for an overview)—little is known about the nature of the resource-demanding processes in PM. Generally, holding an intention has been shown to interfere with the performance of other ongoing activities, and this task interference effect is usually interpreted as evidence for the involvement of resource-demanding processes. The task interference effect has been interpreted as reflecting cue monitoring, preparatory attention, or a strategic allocation of resources in favor of the PM task (cf. McDaniel & Einstein, 2007), but we are aware of only one study that has aimed at further differentiating the processes contributing to the task interference effect (Guynn, 2003).

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Task interference from event-based intentions

In order to study event-based PM in the laboratory, participants are usually presented with an ongoing task that continuously requires responses (e.g., a lexical decision task). Within this task, PM cues are embedded to which participants are instructed to respond with a special action (e.g., pressing the “1” key). Given that both the PM task and the ongoing task draw on the same limited cognitive resource, this paradigm allows for assessing the degree to which resource-demanding processes are involved in PM performance. If having the intention to respond to a PM cue requires attentional resources, then fewer resources should be available to perform the ongoing task. In line with this rationale, ongoing-task performance is often significantly reduced (mostly in terms of slowing in reaction times [RTs]), when participants perform an ongoing task while holding an intention, as compared to participants who perform the ongoing task alone (Cohen, Jaudas, & Gollwitzer, 2008; Hicks, Marsh, & Cook, 2005; Marsh, Hicks, & Cook, 2006b). The degree to which such task interference occurs depends on characteristics of both the ongoing task and the PM task such as the complexity of the ongoing task (Einstein, McDaniel, Williford, Pagan, & Dismukes, 2003) and the time of the occurrence of the PM cue (McBride, Beckner, & Abney, *in press*). Another important factor is the level of additional demands that the PM task imposes on the performance of the ongoing task. The level of these additional demands has been shown to depend on cue features, such as the salience of the PM cues in the context of the stimuli of the ongoing task (Einstein, McDaniel, Manzi, Cochran, & Baker, 2000) or the focality of the PM cues. Cue *focality* refers to the extent to which processing of the ongoing-task stimuli fosters processing of the relevant features of the PM cue (Einstein & McDaniel, 2005; Einstein et al., 2005; Meiser & Schult, 2008; Scullin, McDaniel, Shelton, & Lee, 2010; see also Kliegel, Jäger, & Phillips, 2008 for a recent meta-analysis on cue focality and its effects on aging). Indeed, a substantial body of research has shown that the task interference effect is reduced (sometimes even to a nonsignificant level) and, at the same time, PM performance is increased when the features specifying a PM cue can be processed with little additional cognitive effort (Einstein et al., 2005; Harrison & Einstein, 2010; Hicks et al., 2005; Marsh, Hicks, Cook, Hansen, & Pallos, 2003).

In sum, there is converging evidence that the degree to which an event-based PM task interferes with a specific ongoing task depends on the additional processing demands imposed by the PM task. Here, we suggest that at least two different cognitive processes contribute to this task interference effect: the actual processing demands and the subjectively anticipated demands. On the one hand, the

actual processing demands depend on the degree to which processing of the ongoing-task stimuli fosters detection of PM cues, as outlined above. For example, ongoing-task stimuli can be processed less efficiently when the PM cues are neither overly salient nor focal than when the PM cues are processed as a by-product of performing the ongoing task, because monitoring for the PM cue becomes more effortful. Thus, differences in processing demands of the PM cues contribute to the task interference effect. On the other hand, we suggest that the anticipated task demands play a role for the strategy employed to perform the PM task and the ongoing task. If, for example, participants are aware of the additional demands imposed by the addition of a PM task with the ongoing task, they might adopt a more cautious approach to process ongoing-task stimuli, allowing for more careful cue monitoring. This idea receives empirical support from findings that participants are indeed sensitive to differences in task demands. For example, when the importance of the PM task is stressed, task interference is increased (Marsh, Hicks, & Cook, 2005). Furthermore, Marsh, Cook, and Hicks (2006a) demonstrated that the task interference effect was virtually absent in those blocks of an ongoing task in which participants did not expect PM cues to appear. Apparently, participants in these studies were able to adjust their strategies in approaching the task in accordance with information about the specific demands of the PM task (i.e., in the latter case, information about cue occurrence). In typical investigations of the task interference effect, however, information about task demands provided during intention formation and the actual effort necessary to fulfill the PM task are correlated. Thus, actual processing demands as well as strategic approaches to the performance of the task contribute jointly to the observable behavioral correlates (i.e., more task interference, in terms of slowing in RTs) to unknown degrees. To further disentangle these processes, the present research employs the diffusion model (Ratcliff, 1978) to event-based PM tasks.

Mathematical modeling approaches of cognitive processes have a longstanding tradition in cognitive psychology for decomposing the observable behavioral data into latent cognitive processes and providing process-pure measures of these latent processes. Models of this kind have been fruitfully applied in various areas of psychology to identify underlying cognitive processes, such as multinomial models in decision making and source memory (see Erdfelder et al., 2009, for a review) or signal detection models (e.g., DeCarlo, 2003; Rotello, Macmillan, & Reeder, 2004). In spite of their usefulness in other areas of cognitive psychology, mathematical models are still underrepresented in PM research (but see Smith & Bayen, 2004), however. A general problem that PM research poses for modeling of cognitive processes is the scarce set of observations available for the analysis of PM performance.

In a typical PM experiment, only very few PM trials are included, to maintain the character of the PM cues as rare events (typically not more than 10% of all trials). This greatly reduces the possibilities of disentangling the contributions of different processes to PM performance. As a potential solution, researchers have often turned to the analysis of ongoing-task performance to draw inferences about the processes involved in PM-task performance (e.g., Hicks et al., 2005; Marsh, Hicks, & Cook, 2006b; Marsh et al., 2003). Following this rationale, Horn, Bayen, and Smith (2011) first suggested applying the diffusion model (Ratcliff, 1978) to the data of ongoing-task performance in order to draw more elaborate inferences about the processes involved in PM task performance. While RTs and ongoing-task accuracy have traditionally been analyzed separately, thereby making use of only a subset of the available data, the diffusion model simultaneously considers the whole RT distribution, as well as accuracy data. We will briefly describe the diffusion model and the possible merit of its application to PM research in the next section.

The diffusion model and its application to prospective memory

In general, the diffusion model has been fruitfully applied to a variety of paradigms, giving substantial insight into to the processes involved in fast binary decisions (e.g., Dutilh, Kryptos, & Wagenmakers, *in press*; Ratcliff, Gomez, & McKoon, 2004; Spaniol, Madden, & Voss, 2006; Thapar, Ratcliff, & McKoon, 2003; see also Wagenmakers, 2009, for a recent review). The model decomposes the behavioral data of RTs and accuracy into a set of latent parameters representing the underlying cognitive processes. For that purpose, the model assumes that binary decisions are the result of a set of cognitive processes that can broadly be partitioned into information uptake (i.e., the drift rate ν) and decision criteria. The drift rate represents the amount of information uptake per time unit in favor of one or the other response option. This information uptake process is typically interpreted as the quality of information processing, with higher estimates of the ν parameter representing more efficient information processing. This information

accumulation process starts at a point z somewhere between zero and a and is terminated as soon as the information uptake reaches the upper threshold (parameter a) or the lower threshold (at zero) associated with one of the two response options. As soon as one of the thresholds is reached, the respective response is given by the motor system. If the two response options are associated with the correct and the wrong response, respectively, as in the present application, the parameter z is constrained to $a/2$, because this coding cancels out any bias toward one response option. Furthermore, participants might adopt a more conservative or liberal response criterion—that is, they might accept more or less evidence in favor of one response option before making the response. The more evidence participants consider before making a response, the slower will be the response, but it will also be more accurate, because the systematic influences on the diffusion process exert more influence. This speed–accuracy trade-off is expressed in the separation of the two response thresholds (parameter a). In addition to the information uptake and decision-related parameters, the model also incorporates the contribution of general processes involved in analyzing each stimulus and making the motor response. These processes are captured in the nondecisional RT component (parameter t_0). For example, the time to complete the process of pressing the respective key would enter into the nondecisional RT component, as this process does not vary with stimulus characteristics. The central parameters of the diffusion model are summarized in Table 1. In addition to these core parameters, the model includes further intertrial variability parameters (s_1 , s_2 , s_{t0}).

In the first application of the diffusion model to reanalyze data from a standard event-based PM task, Horn et al. (2011) showed that the addition of a nonfocal and nonsalient PM task, as compared with a condition without a PM task, reduced the efficiency of information uptake (parameter ν). Furthermore, participants in the condition with a PM task adopted a more conservative response criterion (parameter a) in the ongoing task, as compared with participants who did not hold an intention.

Importantly, the application of the diffusion model in PM research requires additional assumptions. First, the model decomposes the processes involved in binary decision

Table 1 Description of the central parameters of the diffusion model

Parameter	Description
Drift rate (ν)	Rate of information uptake per time (higher estimates indicate more efficient information processing)
Upper threshold (a)	Response criterion (higher estimates indicate more conservative responding behavior)
Starting point (z)	Starting point of the diffusion process (if estimated freely, it indicates a responses bias toward one response option)
Reaction time constant (t_0)	Nondecisional reaction time component (represents all nondecisional parts of information processing—e.g., stimulus encoding and response execution)

tasks. The response options in a typical PM experiment, however, are never binary. Participants can either respond to the ongoing task (often a binary task), or they can respond by pressing the special PM key. For the model to be applied to data from PM experiments, the third response option—that is, pressing the PM key—must thus be discarded. This approach might appear somewhat counterintuitive at first glance, since the processes leading to PM responses are the very processes that one aims to model. If one assumes, however, that at the beginning of each trial of the ongoing task, participants are not aware whether or not this trial will include a PM cue, it is reasonable to further assume that participants must execute the same processes at every trial of the ongoing task in order to detect PM cues, and thus to give the respective response.

Therefore, it remains an open question whether the interpretation of the diffusion model's parameters holds when applied to PM tasks. Although the interpretation of the parameters ν and t_0 in the context of PM tasks does not differ from their typical interpretation (Voss, Rothermund, & Voss, 2004), the interpretation of the a parameter diverges from the usual interpretation as a mere speed–accuracy trade-off criterion, and thus warrants particular consideration. In particular, we suggest that the a parameter reflects strategic approaches to performing the PM task in terms of a preparedness to more or less carefully monitor for the PM cue. These strategies are likely to vary as a function of the anticipated demands of the PM task in the context of the ongoing task. Because participants are likely to already be aware of the task demands when forming an intention (Einstein & McDaniel, 2008), they should become more or less cautious in their responding behavior in the ongoing task, depending on the anticipated task demands. In terms of the diffusion model, this implies a different criterion setting (i.e., the parameter a). Thus, the strategic approach to the PM task would manifest itself in the “cautiousness” of participants’ responding behavior.

In their reanalysis, Horn et al. (2011) interpreted the a parameter as reflecting metacognitive beliefs, an idea similar to our conceptualization of the a parameter as reflecting strategic approaches to the performance of the PM task as a function of anticipated task demands. However, Horn and colleagues did not provide empirical evidence that the a parameter selectively captures participants’ strategic task approach in the domain of PM. The fact that the a parameter and the drift rate were affected by the addition of a PM task does not necessarily imply that two different processes were affected, because the a parameter has not yet been shown to measure a specific cognitive process in the context of PM. Therefore, empirical evidence that the a parameter is sensitive to actual changes in participants’ strategic task approaches is needed in order to safeguard this interpretation.

Goals of the present research

The goals of the present research were twofold. First, we aimed to test the psychological validity of the a parameter in a PM context. Earlier research had shown that the diffusion model provides psychologically plausible parameter estimates in binary decision tasks (Voss et al., 2004). As outlined above, however, the application of the diffusion model in the context of PM tasks requires some additional, nontrivial assumptions that require further validation. In the first experiment, we thus aimed at providing empirical evidence for the validity of our interpretation of the parameter a as reflecting the strategic approach to the PM task, by manipulating the anticipated task demands while holding the actual task demands constant.

The second goal was to disentangle the processes involved in creating the task interference effect in PM by applying the diffusion model to PM tasks of different levels of task demands. In the second experiment, we built on the evidence for the validity of the a parameter as reflecting strategic task approaches and applied the model to disentangle the processes contributing to the task interference effect in PM. The degree to which the different processes changed by the addition of a PM task could be assessed by comparing parameter estimates of ongoing-task performance between a condition with an embedded PM task and a condition without a PM task. Furthermore, the comparison of ongoing-task performance between two conditions that differed with regard to the cognitive demands posed by the PM task could illuminate which cognitive processes underlie the task interference effect. In particular, we argue that the ν parameter and the a parameter can be interpreted as the two distinct processes contributing to the task interference effect outlined earlier. First, anticipated PM task demands might lead participants to establish different strategic approaches to the performance of the PM task during intention formation. In terms of the diffusion model, this should be reflected by changes in the a parameter.

Second, actual additional demands imposed by the PM task should be reflected by the degree of overlap of the processes required for performance in the ongoing task and PM performance (cf. Einstein & McDaniel, 2005). In terms of the diffusion model, similar processing demands for both tasks would be expected to leave the information uptake (i.e., the drift rate ν) relatively unaffected, while less similar processing demands should impede the information uptake, because the different stimulus features must be processed for the ongoing task and the PM task (Horn et al., 2011). This interpretation receives empirical support from a study manipulating the processing difficulty of stimuli that affected the ν parameter (Voss et al., 2004). In this study, participants

were asked to decide which of two colors was dominant in a briefly presented colored square. The condition with the more similar ratio of the two colors in the square resulted in a lower drift rate than in the condition with the less similar ratio of the two colors. This selective effect on the drift rate parameter thus lends psychological validity to the interpretation of the parameter as reflecting the efficiency of information processing.

Experiment 1

To show that the parameter a is sensitive to explicit changes in the strategic task approach, we manipulated the anticipated task demands in [Experiment 1](#) directly, while holding the actual demands of the PM and ongoing tasks constant. For that purpose, participants in one group were informed during intention formation that it was very unlikely that PM cues would appear during the ongoing task, whereas in a second group, participants were informed that it was very likely that PM cues would appear. In fact, all participants were presented with PM cues. We expected participants in the first group to adopt a less conservative response criterion (parameter a) than participants in the second group, because participants in the first group should deem it unlikely that cues will appear and thus be less cautious in their cue-monitoring approach. The PM task employed in both groups used cues that were neither focal nor overly salient, and thus PM performance should require resource-demanding processes (e.g., Einstein et al., 2005; Smith & Bayen, 2004). Importantly, the *actual* task demands did not differ between both groups, so we expected an effect on neither the drift rate (parameter ν) nor the nondecisional RT constant (parameter t_0). In sum, if the interpretation of the a parameter as reflecting the anticipated task demands is valid, the present manipulation should only be reflected in differences in the a parameter, leaving the other parameters unaffected. Thus, an effect of our manipulation on the a parameter in the predicted direction would be evidence for the convergent validity of our interpretation of the a parameter, whereas a lack of an effect on the other parameters would be evidence for its divergent validity.

Method

Participants A total of 64 students, of whom none were colorblind, were tested in sessions with up to 5 participants. Participants received course credit or monetary compensation and were randomly assigned to one of the two experimental conditions described above.

Materials A color-matching task served as the ongoing task (Smith & Bayen, 2004). On each trial of this task,

participants were presented with a series of four colored rectangles, followed by a colored probe word. Participants had to decide whether the color of the probe matched the color of one of the rectangles that had previously been presented. Six colors were selected for the color-matching task: blue, green, white, cyan, yellow, and red. The colored rectangles appeared in the center of the screen on a black background. Probe words were also presented in the center of the screen in 24-point colored letters on a black background. Each rectangle was presented for 350 ms, followed by a 250-ms blank screen. The words remained on the screen until a response was entered. At the end of each trial, participants were asked to press the space bar to proceed to the next trial. For this task, 182 words of medium written frequency were randomly selected from a German word norm database. From this pool, a set of six words were randomly drawn and served as PM cues in both conditions. The remaining words were used as neutral stimuli in the ongoing task.

Procedure The experiment started with instructions for the color-matching task, which emphasized both speed and accuracy. Participants were asked to press the “J” key if the color of the word matched the color of one of the four rectangles presented prior to the word, and to press the “N” key if the color of the word does not match any of the rectangles. Following these instructions, participants completed six practice trials and were then given the opportunity to ask questions. The subsequent PM instructions asked the participants to press the “1” key whenever one of six words they would next study appeared in the color-matching task, and the participants were next asked to press the “1” key to ensure that they would find the right key. Then the six PM cue words were presented serially in the center of the screen for 5 s each. Participants in the low-PM-expectancy group were then informed that study words would appear only for 10% of all participants. Participants in the high-PM-expectancy group were informed that the study words would appear for 90% of all participants. Before starting with the color-matching task, participants completed a computer-based filler task for 5 min to prevent them from rehearsing the PM cues. For the filler task, participants were randomly presented with a letter in the center of the screen, and the task was to press the key for the letter two letters later in the alphabet. Subsequently, they performed 182 trials of the color-matching task. Half of the trials were match trials and the other half were nonmatch trials, with both kinds of trials randomly intermixed. For all participants, PM cues were presented at Trials 26, 52, 78, 104, 130, and 156; half of the PM trials were match trials and half were nonmatch trials. The order of match and nonmatch PM trials was also determined randomly. At the end of the color-matching task, partic-

ipants were asked to recall the PM task and were debriefed and dismissed.

Results

Data from participants who did not recall the PM task and never gave a correct PM response were excluded from all analyses. The final sample consisted of 31 participants in the high-expectancy group and 30 participants in the low-expectancy group.

The level of statistical significance was set to .05 for all analyses.

Diffusion model analyses Parameter estimates and goodness-of-fit tests were conducted with the computer program fast-dm (Voss & Voss, 2007). We fitted one model for each participant. Statistical inferences concerning parameters were based on comparisons of mean estimates across groups. In order to assess the goodness of fit of the diffusion model to the data, we performed individual tests of fit separately for each participant via Kolmogorov–Smirnov tests (Voss & Voss, 2008). None of the 61 tests was significant at or below the .05 level, indicating that model assumptions were not violated.

Only RTs and accuracy data from non-PM trials served as data for the diffusion model analyses. All responses below 300 ms, as well as all responses two standard deviations above each participant's individual mean, were discarded prior to parameter estimation (4% of all trials). After this correction for aberrant RTs, between 156 and 165 trials per participant were available for parameter estimation. The upper threshold in the model was associated with the correct response in the color-matching task, and the lower threshold was associated with the incorrect response. The parameter z was set to $a/2$ because this coding of responses cancels out any possible response bias. In sum, the three core parameters (a , v , and t_0), and three intertrial variability parameters (s_z , s_v , and s_{t0}) were estimated. Table 2 displays the mean parameter estimates for both groups. In the next step, we compared mean parameter estimates across groups.

An independent-samples t test revealed a significantly higher upper threshold parameter (a) in participants in the high-expectancy group ($M = 2.18$, $SE = .09$) than in participants in the low-expectancy group ($M = 1.92$, $SE = 0.09$), $t(59) = 2.06$, $p = .04$, $d = 0.47$. This result implies that participants in the high-expectancy group were significantly more cautious in their responding behavior than participants in the low-expectancy group.

The same test on the drift rate (v) revealed no difference in the quality of information processing between the high-expectancy group ($M = 1.30$, $SE = 0.08$) and the low-expectancy group ($M = 1.33$, $SE = 0.11$), $t(59) < 1$. There was also no difference in the

nondecisional RT component (t_0) between the high-expectancy ($M = 0.71$, $SE = 0.04$) and low-expectancy ($M = 0.72$, $SE = 0.03$) groups, $t(59) < 1$.¹

Prospective memory performance We scored any presses of the “1” key occurring at any time between the presentation of a PM cue and the presentation of the next word as a correct PM response. A t test on the proportions of correct PM responses revealed that PM accuracy did not differ significantly between the conditions with high expectancy ($M = .34$, $SE = .05$) and low expectancy ($M = .24$, $SE = .05$) of PM occurrence, $t(59) = 1.5$, $p = .14$, $d = 0.38$. However, the power of this test was only $1 - \beta = .31$.² In order to detect an effect of this size with reasonable power (i.e., $1 - \beta = .80$), a total of 220 participants would be required. Alternatively, the effect might be more pronounced when using a stricter criterion for scoring correct PM responses. Late PM responses could be partially based on discrepancy-plus-search processes (McDaniel et al., 2004) initiated after the cue has been processed. Thus, late PM responses are probably less affected by differences in anticipated task demands. We therefore computed the proportions of correct responses to a PM cue as pressing the “1” key on PM trials only and excluded all later responses to the PM cue. Indeed, a t test on immediate PM responses yielded a significantly higher PM accuracy in the condition with high expectancy of PM occurrence ($M = .33$, $SE = .05$) than in the condition with low expectancy of PM occurrence ($M = .19$, $SE = .04$), $t(59) = 1.5$, $p = .027$, $d = 0.58$.³

Performance in the ongoing task Accuracy and mean RTs in the color-matching task were used as the dependent variables.⁴ The means of the accuracy scores in each condition are presented in Table 3. An independent-samples t test on the accuracy scores showed that ongoing-task accuracy did not differ significantly between the high-expectancy and low-expectancy groups, $t(59) < 1$.

For the RT analysis, only accurate responses and responses slower than 300 ms but faster than two standard deviations above each participant's individual mean were

¹ Although descriptively the differences between both groups in mean parameter estimates of t_0 and v were negligible, analyses with a hierarchical diffusion model (Vandekerckhove, Tuerlinckx, & Lee, 2011), which considers the distribution of mean parameter estimates, might have been more powerful for detecting effects in these parameters. We thank an anonymous reviewer for drawing our attention to this issue.

² Power analyses were conducted with the program G*Power (Faul, Erdfelder, Lang, & Buchner, 2007).

³ We thank an anonymous reviewer for suggesting this additional analysis.

⁴ The very first trial and the first trial following each PM trial were excluded from the analysis of the color-matching task in order to avoid finding artifactual costs associated with these trials.

Table 2 Average parameter estimates (and standard deviations) for Experiments 1 and 2

Diffusion Model Parameter	Experiment 1		Experiment 2		
	High PM Expectancy	Low PM Expectancy	Demanding PM Task	Nondemanding PM Task	Control Group
a	2.18 (0.53)	1.92 (0.48)	2.05 (0.33)	1.77 (0.41)	1.81 (0.42)
v	1.30 (0.46)	1.33 (0.59)	1.28 (0.36)	1.53 (0.60)	1.61 (0.56)
t_0	0.71 (0.21)	0.72 (0.15)	0.72 (0.20)	0.59 (0.14)	0.61 (0.12)
s_{t0}	0.46 (0.34)	0.40 (0.24)	0.44 (0.36)	0.27 (0.15)	0.24 (0.18)
s_v	0.32 (0.36)	0.23 (0.21)	0.24 (0.20)	0.45 (0.37)	0.46 (0.31)
s_z	0.78 (0.50)	0.60 (0.42)	0.62 (0.34)	0.37 (0.25)	0.52 (0.31)

included in the analyses, to control for aberrant RTs (Ratcliff, 1993). Mean RTs in each condition are presented in Table 3. An independent-samples t test on the mean RTs revealed that the high-expectancy group ($M = 1,397$, $SE = 65$) and the low-expectancy group ($M = 1,278$, $SE = 59$) did not differ significantly, $t(59) = 1.54$, $p = .13$, $d = 0.35$.

Although it could be expected that participants in the high-expectancy condition would exhibit slower responding behavior than participants in the low-expectancy condition, this effect might have been diminished after participants detected a PM cue for the first time. In order to investigate this possibility, we compared, for each group separately, mean RTs before a participants' individual first detection of a PM cue with those after their first detection of a PM cue. One-tailed comparisons revealed that participants in the high-expectancy group showed a practice effect in terms of significantly slower RTs before ($M = 1,541$, $SE = 70$) as compared to after ($M = 1,381$, $SE = 77$) the first cue detection, $t(23) = 1.96$, $p = .031$. Participants in the low-expectancy group, however, did not show any change in RTs from before ($M = 1,496$, $SE = 85$) to after ($M = 1,470$, $SE = 113$) first detection of a PM cue, $t(23) = 0.31$, $p = .379$. This result suggests that participants in the low-expectancy group, once they realized that they would be presented with cues despite their expectation, devoted more resources to cue detection, counteracting an ongoing-task practice effect. Participants in the high-expectancy group, however, already expected cues to appear and thus did not need to change their resource allocation after they detected the first cue; instead, participants in this group showed a practice effect, as is typically observed in the

color-matching task (Rummel, Boywitt, & Meiser, *in press*; Smith & Bayen, 2004).

Discussion

The results from the first experiment provided strong evidence that the a parameter can indeed be interpreted as a measure of cautiousness in stimulus processing, reflecting expectations about the demands imposed by the PM task. The parameter responded as predicted to our manipulation of expectancies regarding the probability of PM cue appearances: Participants who thought it unlikely that the PM cue would be presented in the ongoing task set their decision criterion (parameter a) significantly lower than those who expected that PM cues would be presented with a high probability. Importantly, the other parameters were not affected by this manipulation, indicating that the a parameter is selectively sensitive to anticipated task demands. Providing divergent validity, neither the drift rate nor the nondecisional RT component differed between the conditions, reflecting the fact that actual task demands also did not differ between the conditions. These results warrant our interpretation of the a parameter as reflecting the strategic task approach established to meet anticipated task demands.

In line with the less cautious responding behavior in the group with the low PM cue expectations, PM performance was also lower in this group than in the high-expectancy group. This result suggests that if resources are necessary for PM performance and participants underestimate the PM task demands (or are led to underestimate them), PM performance is hampered.

Table 3 Mean ongoing-task reaction times (and standard deviations; in milliseconds) and mean ongoing-task accuracy (and standard deviations)

	Experiment 1		Experiment 2		
	High PM Expectancy	Low PM Expectancy	Demanding PM Task	Nondemanding PM Task	Control Group
Accuracy	.88 (.09)	.88 (.11)	.89 (.06)	.87 (.09)	.89 (.08)
Reaction times	1,397 (316)	1,278 (284)	1,359 (336)	1,031 (221)	1,055 (192)

Experiment 2

Based on the results of [Experiment 1](#), in [Experiment 2](#) we aimed at disentangling the effects of differences in the additional PM task-demands on the task interference effect, in terms of the diffusion model parameters. Previous research had shown that the task interference effect is moderated by the processing difficulty of the PM cue in the context of an ongoing task. To reiterate, the task interference effect can be significantly reduced, and PM performance is likely to increase, when PM cues become more salient and focal (Einstein et al., 2005; McDaniel et al., 2004; Scullin et al., 2010). To investigate the contributions to the task interference effect of the two latent processes of expectations about task demands and the actual processing demands of the PM cues, we adopted a nondemanding PM task condition with salient and focal cues and compared it with a rather demanding PM task condition equivalent to the one used in the first experiment. Additionally, we utilized a condition in which participants performed the ongoing task alone as a baseline for estimating the absolute contributions of the processes to PM performance.

We hypothesized that the demanding but not the nondemanding PM task should decrease the efficiency of information uptake (parameter ν) in the ongoing task. Additionally, if participants were aware of the additional demands of the PM tasks, this manipulation should also affect the cautiousness with which the task would be approached (parameter a). Furthermore, it was an open question whether the t_0 component would be affected by the manipulation of task demands. In their first application of the diffusion model to PM data, Horn et al. (2011) did not find effects on the t_0 component when comparing a PM task of medium demands (cf. Cohen et al., 2008) with a control group without a PM task. However, Horn and colleagues suggested that with further increased PM demands, participants might start checking for PM cues constantly on each trial in addition to their ongoing-task decision (Guynn, 2003), and these differences in cue checking might be reflected by the t_0 component.

Method

Participants A total of 90 students, of whom none were colorblind, were tested in sessions with up to 5 participants. Participants received monetary compensation and were randomly assigned to one of the three conditions.

Materials and design The materials were the same as those in the first experiment, with the following exceptions. The same six words as in [Experiment 1](#) served as PM cues for the demanding PM condition. In the nondemanding PM

condition, a string of red Xs served as the PM cues. Importantly, while none of the probe words were presented in red color in any condition, only the PM cues in the nondemanding PM condition (i.e., the string of Xs) were red. Notably, these Xs were the only red probes in the color-matching task. Because the ongoing task required color decisions, the processes for performing the ongoing task and detecting the PM cues were very similar, thus rendering the PM task focal and salient (cf. Rummel et al., *in press*). In the control condition, no PM task was included.

Procedure The instructions for the color-matching task were identical to those used in the first experiment. After the ongoing-task instructions, participants in the control condition received no further instructions and went on to a delay activity. Participants in the two PM conditions were instructed to react to PM cues in the color-matching task by pressing the “1” key whenever a PM cue appeared. Subsequently, the participants were asked to press the “1” key to ensure that they would find the right key.

In the instructions for the demanding PM task, participants were presented with the six PM cues serially in the center of the screen in 24-point black letters for 5 s each, each presentation separated from the next by a blank screen for 250 ms. In the nondemanding PM task, participants were presented with the strings of red Xs for 5 s, which served as the PM cue. Subsequently, participants in all conditions completed the same computer-based filler task used in the first experiment for 5 min. Then, participants completed the color-matching task without any further mention of the embedded PM task. At the end of the experiment, participants were asked to recall the PM task and were then debriefed and dismissed.

Results

Data from participants who did not recall the PM task and never gave a correct PM response were excluded from all analyses. The final sample consisted of 26 participants in the demanding-PM-task group, 30 participants in the nondemanding-PM-task group, and 30 participants in the control group.

Diffusion model analyses The same outlier exclusion criteria used in [Experiment 1](#) led to the exclusion of 1% of all trials. After correction for aberrant RTs, between 153 and 168 trials per participant were available for parameter estimation. Model specification and parameter estimation was conducted analogously to [Experiment 1](#). Table 2 displays mean parameter estimates across conditions.

None of the 86 individual model fit tests were significant at or below the .05 level. We then compared mean parameter estimates across the three conditions via planned contrasts corresponding with our hypotheses. The first contrast juxtaposed the demanding PM group against both the nondemanding PM group and the control group, and the second contrast juxtaposed the nondemanding PM group against the control group.

The overall F test on the upper-threshold parameter (a) was significant, $F(2, 83) = 4.06$, $p = .02$, $\eta_p^2 = .09$. Planned contrasts revealed that the nondemanding PM group and the control group showed significantly lower a values than the demanding PM group, $t(83) = 2.82$, $p = .006$, $d = 0.62$, but the nondemanding PM group and the control group did not differ significantly, $t(83) < 1$. Thus, participants were sensitive to the task demands in their strategic task approach. While participants in the demanding PM group were rather conservative in their response behavior, participants in the nondemanding PM group and the control group were less so.

Furthermore, overall differences in the drift rate (v) were marginally significant, $F(2, 83) = 3$, $p = .06$, $\eta_p^2 = .07$. Again, planned comparisons revealed that the nondemanding PM group and the control group exhibited significantly higher drift rates than the demanding PM group, $t(83) = 2.36$, $p = .02$, $d = 0.58$, but the nondemanding PM group and the control group did not differ significantly, $t(83) < 1$. As hypothesized, the demanding PM task led to reduced processing efficiency as compared to the less demanding PM task. In fact, the processing efficiency in the nondemanding PM group was comparable to the processing efficiency observed in the control group, which is evidence that processing of salient and focal cue was effortless (Einstein & McDaniel, 2005).

Interestingly, the omnibus F test on the nondecisional RT component (t_0) was also significant, $F(2, 83) = 5.34$, $p = .006$, $\eta_p^2 = .11$. Contrasts revealed that the nondemanding PM group and the control group exhibited a significantly lower nondecisional RT component than the demanding PM group, $t(83) = 3.25$, $p = .002$, $d = 0.71$, but the nondemanding PM group and the control group did not differ significantly, $t(83) < 1$. This is first evidence that the t_0 component might reflect processes contributing to PM performance, as suggested by Horn et al. (2011). We will turn to this result in the Discussion section below.

Prospective memory performance A t test on the proportions of accurate PM responses (i.e., pressing the “1” key in response to a PM cue) revealed that PM accuracy was significantly higher in the nondemanding PM condition ($M = 1$, $SE = 0$) than in the demanding PM condition ($M = .32$, $SE = .06$), $t(54) = 12.36$, $p < .001$, $d = 3.36$. As expected, the nondemanding PM task resulted in higher,

and in fact ceiling, PM accuracy, while the performance in the demanding PM task was similar to that in Experiment 1.

In order to further elucidate the functional relationship of model parameters to PM processes, we conducted additional correlation analyses between parameter estimates and PM performance.⁵ Because PM performance was factually at ceiling in the nondemanding PM condition, correlation analyses were restricted to the demanding PM condition. As expected, more cautious responding behavior was associated with higher PM performance, as indicated by positive correlation between PM performance and the a parameter, $r(26) = .43$, $p = .027$. The drift rate, however, was not significantly associated with PM performance, $r(26) = -.20$, $p = .33$, suggesting that the task demands, which of course were identical for all participants, were not functionally related to PM performance. Adding further evidence to the potentially functional role of the nondecisional RT component, this parameter was positively associated with PM performance, $r(26) = .54$, $p = .005$. Thus, under demanding PM task conditions, both the process reflected by the response criterion and (some of) the processes reflected by the nondecisional RT component seem to be functional for PM performance.

Performance in the ongoing task Analogously to the first experiment, accuracy and mean RTs in the color-matching task were used as dependent variables. The means of the accuracy scores and RTs in each condition are presented in Table 3. A one-way ANOVA with Condition (nondemanding PM task vs. demanding PM task vs. control) as a between-participants factor on the accuracy scores showed that ongoing-task accuracy did not vary as a function of condition, $F < 1$. Accordingly, inclusion of a PM task did not lead to diminished accuracy in the ongoing task.

For the RT analysis, the same outlier exclusion criteria were applied as in Experiment 1. The omnibus F test on these mean RTs across groups was significant, $F(2, 83) = 14.2$, $p < .001$, $\eta_p^2 = .25$. Planned contrasts showed that participants in the demanding PM condition were significantly slower as compared to those in the control and nondemanding PM conditions combined, $t(83) = 5.32$, $p < .001$, $d = 1.17$. Additionally, the nondemanding condition did not differ significantly from the control condition, $t(83) < 1$. In sum, the contrast analysis on RTs showed a significant task interference effect in the demanding PM condition as compared to the control condition. Importantly, in the nondemanding task condition, interference was signifi-

⁵ We thank an anonymous reviewer for suggesting these additional analyses.

cantly reduced as compared to the demanding PM condition, and ongoing-task performance in the nondemanding group was on a level similar to that in the control condition.

Taken together, the traditional analyses replicated the well-established task interference effect with demanding PM tasks: PM performance was lower with nonsalient, nonfocal cues, while RTs to the ongoing task were simultaneously slowed.

Discussion

The second experiment shows that at least two different cognitive processes contribute to the task interference effect observed as a function of task demands. These processes are (1) the actual additional processing demands a PM task imposes on the ongoing task and (2) the strategic approach to the performance of the task. We argued on the basis of [Experiment 1](#) that the response criterion is set during intention formation and that it reflects an a priori awareness of the additional demands from the PM task (cf. Einstein & McDaniel, 2008). For [Experiment 2](#), we hypothesized that the manipulation of task demands would affect not only the actual processing demands, but also the anticipated demands. If participants perceived the PM task to be relatively easy, they might adopt a less conservative response criterion—that is, they might be less cautious in their responding—than when they perceived the PM task to be less easy. The results from the present experiment offer clear evidence for this assumption. On the behavioral level, the manipulation of the task demands replicated the typical finding, with higher PM accuracy and faster ongoing-task performance with the nondemanding PM task than with the demanding one. Diffusion model analysis of ongoing-task performance showed that this task interference effect in the demanding PM condition was due to differences in the drift rate and in the response criterion. As predicted, participants benefited from reduced task demands in the nondemanding PM task in terms of more effective information uptake (i.e., drift rate). Additionally, they also adopted a less conservative response criterion in the less demanding as compared to the more demanding PM condition, suggesting some awareness of differences in the additional demands imposed by the PM task. Furthermore, the response criterion did not differ between the control condition and the less demanding PM condition; that is, participants in the latter condition were similarly cautious in their response behavior as those in the control condition who did not hold an intention. Correlation analyses further supported the notion that participants' cautiousness in making a response was functionally related to PM performance in the demanding PM task condition. These results are in

line with our interpretation of the a parameter as reflecting strategic approaches to task performance, whereas the drift rate represents task demands, which were the same for all participants in the demanding PM task condition.

Besides the actual processing demands and the anticipated task demands, which were expected to contribute to the task interference effect, there was also an effect of the variation of PM task demands on the nondecisional RT component (i.e., t_0). Participants in the nondemanding PM task condition and the control condition were faster in ongoing-task performance than were participants in the demanding PM condition, by a constant additive factor. Further correlation analyses indicated that the t_0 component in the demanding PM condition was significantly correlated with PM performance. This is evidence that this component also reflects processes that are functional for PM performance, as suggested by Horn et al. (2011). In particular, based on the idea that, under demanding PM task conditions, individuals tend to constantly check for PM cues in addition to their actual ongoing-task decision (cf. Guynn, 2003), Horn and colleagues argued that such cue checking should be reflected by the t_0 component. Recently, it has been pointed out that the t_0 component reflects all nondecision aspects of information processing, including not only response execution but also stimulus encoding (Voss, Voss, & Klauer, 2010). Thus, variations in the t_0 component may also include variations in encoding times of ongoing-task stimuli. A generally slower encoding of ongoing-task stimuli could be due to an increased engagement in checking for the PM cue on each trial. Because the t_0 component comprises variations in response execution as well as variations in encoding times, this parameter might not provide a process-pure measure of a specific PM process. However, because there was a significant correlation between the t_0 component and PM performance under demanding PM task conditions, it seems likely that this component (partially) reflected differences in the engagement of functional cue-checking processes.

General discussion

The task interference effect caused by holding an intention can be reduced or even dispersed by implementing less demanding PM tasks, such that the processing demands of the ongoing task and the PM task overlap. Our results suggest that this effect is due to two distinct cognitive processes: (1) reduced processing demands due to the increased task overlap of the PM and ongoing tasks, and (2) different strategic approaches to meet the (anticipated) processing demands.

In the first experiment, we validated the a parameter as reflecting strategic approaches to the performance of a PM task in a given ongoing task as a function of the anticipated task demands. In doing so, we provided original evidence for the interpretation of this parameter as reflecting metacognitive PM strategies, an idea that has been discussed before (cf. Horn et al., 2011) but has not yet been addressed empirically. We showed that the a parameter was selectively affected by the participants' expectancies about the probability of PM cue occurrence. Importantly, the actual processing demands did not differ between the two groups, suggesting that the a parameter indeed reflects differences in strategic approaches to the task. These results set the stage for a more complete scrutiny of the task interference effect in the second experiment. In Experiment 2, we replicated the results typically found in studies manipulating the quality of PM cues: PM performance decreased with the decreased salience and focality of the PM cues, and at the same time PM-induced interference with ongoing activities increased. Diffusion model analyses, however, provided substantial insight into *why* this task interference would be observed: Participants not only exhibited less efficient processing of the ongoing task (lower v parameter) with the embedded demanding PM task, they also adopted a less liberal response criterion (higher a parameter). Additionally, there was some evidence that they might also have engaged in more careful checking for PM cues on each trial (higher t_0 component).

These findings are in line with recent research discussing the role of metacognitive awareness about task demands and its consequences for task interference effects in PM (Einstein & McDaniel, 2008). The general idea is that individuals are already aware of the to-be-expected task demands when they form an intention and that they use this awareness when they approach the task. However, so far little is known about how aware individuals are of real task demands. Einstein and McDaniel (2008) reported results from an unpublished study using a meta-PM questionnaire with hypothetical PM situations, providing the first evidence that people are to some extent sensitive to reduced PM task demands in real-life scenarios. In line with this notion, the more liberal response criterion in the presence of a PM task with salient and focal cues in Experiment 2 suggests that participants were at least somewhat aware of the different actual task demands in the demanding and nondemanding PM task conditions. Future research that included subjective measures to assess anticipated task demands directly could provide further insights into the precision of this awareness.

On a methodological level, we extended the application of the diffusion model to the PM paradigm of Horn

et al. (2011). Going beyond the reanalysis reported by Horn and colleagues, Experiment 1 provided original evidence that the response criterion parameter (a) of the diffusion model can be manipulated independently from the other parameters in a theoretically meaningful manner, and that this parameter reflects anticipated processing demands. Methodologically, the present research highlights the importance of parameter validation in the modeling of cognitive processes. Effects on model parameters must not be interpreted as reflecting distinct cognitive processes unless these parameters have been shown to be sensitive to the very processes they are supposed to measure (cf. Rummel et al., *in press*). Second, Experiment 2 demonstrated that the parameters of the diffusion model can provide insight into the processes affected by manipulations of the salience and focality of PM cues, which are well established in the PM literature. Nonetheless, one must be willing to make additional assumptions in the interpretation of the model's parameters when they are applied to PM data. Because only data from ongoing-task performance serve as the input data for parameter estimation, it must be assumed that the same processes take place on non-PM and PM trials. We believe, however, that this assumption can at least indirectly be tested by comparing parameter estimates between a control condition without a PM task and a condition with a PM task, as was done here. Furthermore, correlations of model parameters and PM performance measures can further safeguard the interpretation of parameters as reflecting processes functional for PM performance. Therefore, we believe that the diffusion model provides a powerful method that can help gain a better understanding of which underlying cognitive processes are affected by different manipulations of the PM task and the ongoing task. This study was another step in a series of methodological proposals toward disentangling the processes that contribute to PM performance.

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