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Arousal, exploration and the locus coeruleus-norepinephrine system
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Chapter 7

Temporal expectation and information processing: A model-based analysis

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Temporal expectation and information processing: A model-based analysis.

Abstract

People are able to use temporal cues to anticipate the timing of an event, enabling them to process that event more efficiently. We conducted two experiments, using the fixed-foreperiod paradigm (Experiment 1) and the temporal-cueing paradigm (Experiment 2), to assess which components of information processing are speeded when subjects use such temporal cues to predict the onset of a target stimulus. We analyzed the observed temporal expectation effects on task performance using sequential-sampling models of decision making: the Ratcliff diffusion model and the shifted-Wald model. The results from the two experiments were consistent: temporal expectation affected the duration of nondecision processes (target encoding and/or response preparation) but had little effect on the two main components of the decision process: response-threshold setting and the rate of evidence accumulation. Our findings provide novel evidence about the psychological processes underlying temporal expectation effects on simple- and choice-reaction time.

Introduction

People are able to use temporal cues to anticipate with great precision the timing of an event, enabling them to optimize the processing of that event. For example, people can use the onset of amber traffic lights to direct the temporal focus of attention towards the moment in time in which the lights will turn green (or red, depending on the region of the world they are in), allowing them to speed up their response to the green signal. Experimental psychologists have long known that response times (RTs) are faster if a target is preceded by a warning signal that is presented at a constant, or at least predictable, temporal delay (reviewed in Hackley, 2009; Niemi & Näätänen, 1981; Nobre, Correa, & Coull, 2007). This beneficial effect is also observed for choice RTs, even though the warning signal contains no information about the identity of the upcoming stimulus. The ability of people to use temporal cues is also evident in the brain: neurons in several brain areas encode the probability that a stimulus will occur at any given point in time (Ghose & Maunsell, 2002; Janssen & Shadlen, 2005; Riehle, Grün, Diesmann, & Aertsen, 1997). The goal of the current study was to increase our understanding of *which components of information processing* are speeded when people can predict the onset of a target stimulus.

The effects of temporal expectation on task performance have been studied with two different paradigms, developed in largely separate literatures. One is the foreperiod paradigm, in which the warning signal is a perfect predictor of the interval (or *foreperiod*) between the onsets of the warning signal and the target. Foreperiod duration is typically varied between blocks of trials. The typical finding in this paradigm is that RTs increase progressively as the duration of the foreperiod is increased and therefore harder to estimate (Klemmer, 1956; Niemi & Näätänen, 1981)⁶. The other paradigm is the temporal-cueing paradigm, in which a cue predicts with some certainty (e.g., 80%) the interval between the onsets of the cue and the target. The *cue-target interval* is varied within blocks of trials. The typical finding in this paradigm is that RTs are faster when the cue-target interval is validly cued (i.e., confirms the participant's expectation) than when the interval is invalidly cued (Correa, Lupiáñez, Milliken, & Tudela, 2004; Coull & Nobre, 1998). The manipulation within blocks of cue-target intervals and the dissociation of expected and actual cue-target intervals (on invalidly cued trials) make the temporal-cueing paradigm more suitable for event-related fMRI studies, which have examined the brain areas that are activated when people process the temporal cue and orient their attention (reviewed in Coull, 2004). However, it seems reasonable to assume that the key behavioral effects obtained in the two paradigms reflect similar underlying mechanisms: in both paradigms participants are required to voluntarily orient their attention to particular moments in time; and experimental manipulations (foreperiod duration or cue validity) affect the degree to which participants are prepared at the moment when the target is presented.

⁶ We only consider foreperiods ≥ 400 ms. At shorter foreperiods target processing can benefit from the phasic increase in arousal elicited by the presentation of the warning stimulus: an *accessory stimulus effect* (Hackley & Valle-Inclán, 1998; Jepma, Wagenmakers, Band, & Nieuwenhuis, 2009)

Which aspects of information processing are responsible for the decrease in RTs as temporal certainty increases? One possible account is that temporal certainty facilitates encoding of the target (cf. Jepma, Wagenmakers, Band, & Nieuwenhuis, 2009; Niemi & Näätänen, 1981). Another possibility is that temporal certainty affects a critical parameter of the decision process that is based on the sensory evidence obtained during stimulus encoding. The mechanism underlying two-choice decisions is well described by the accumulation of noisy information from a stimulus over time (Gold & Shadlen, 2007; Smith & Ratcliff, 2004). Information accumulates toward one or the other of two decision thresholds until one of the thresholds is reached; then the response associated with that threshold is initiated. It is possible that orienting attention to the moment of target onset, or a timed phasic increase in arousal, speeds up the rate with which evidence is accumulated in the decision process (cf. Grosjean, Rosenbaum, & Elsinger, 2001). Another possibility is that increased temporal certainty does not change the rate of information build-up but instead causes a lowering of the decision threshold (or, equivalently, a rise in starting point; Bogacz, Wagenmakers, Forstmann, & Nieuwenhuis, 2010). That is, participants begin to decrease the threshold in anticipation of the target. As a result, responses are faster because decisions are made on the basis of less evidence (Posner, 1978). A final account assumes that increased certainty about the timing of an upcoming target can be used to prepare the motor system, without committing to any particular response (Bertelson, 1967; Sanders, 1980). This may speed up the execution of a specific motor response to the target, much like a pre-heated engine will make a car start quicker in any direction.

Previous research has found substantial evidence regarding the locus of temporal certainty effects: To examine the response execution account, researchers have conducted choice-RT experiments that examined the effect of foreperiod on the lateralized readiness potential (LRP), a difference wave that indexes hand-specific response preparation. The onset of the LRP indicates the moment at which the motor cortex associated with the responding hand becomes more active than the ipsilateral motor cortex, an early indication of the forthcoming motor response. The general finding is that the effect of foreperiod on the interval between LRP onset and the overt response is small or absent, which has led researchers to conclude that there is very little evidence for a foreperiod effect on the duration of motor preparation and execution (e.g., Hackley, Schankin, Wohlschlaeger, & Wascher, 2007; Müller-Gethmann, Ulrich, & Rinkeauer, 2003). However, Tandonnet and colleagues have suggested that these LRP findings may be misleading. They examined the Laplacian-transformed event-related potential (ERP) waveforms to obtain separate estimates of the ipsilateral and contralateral motor cortex response. Although effect sizes were modest, Tandonnet and colleagues found that increased temporal certainty decreased the time between the onset of the contralateral negativity indexing the motor command and the electromyographic (EMG) onset (Tandonnet, Burle, Vidal, & Hasbroucq, 2003, 2006), suggesting a speedup of motor preparation. When they used the same data to compute the monopolar (i.e. standard) and the Laplacian LRPs, they found no foreperiod effect on the LRP-to-response interval. This suggests that the double-subtraction methods used to compute the LRP can obscure subtle latency effects present in the constituent ERP waveforms. Tandonnet and colleagues further found

that increased temporal certainty shortened the time between EMG onset and the actual key press (Tandonnet et al., 2003; see also Hasbroucq, Akamatsu, Mouret, & Seal, 1995). This indicates that temporal certainty can also influence the duration of motor execution.

While there are small but robust effects of temporal certainty on the duration of motor processes, these effects cannot fully account for temporal expectation effects on RT. In particular, several studies have found that increased temporal certainty reduces the interval between the stimulus and the P3/LRP onset, two established markers of the combined duration of stimulus encoding and decision making (Correa, Lupiáñez, Madrid, & Tudela, 2006; Müller-Gethmann et al., 2003). These studies suggest that temporal expectation effects on RT must also have an earlier locus.

Temporal certainty improves various aspects of perception (Bausenhart, Rolke, & Ulrich, 2008; Martens & Johnson 2005; reviewed in Nobre et al., 2007). Importantly, it also improves performance in psychophysical variants of the two paradigms discussed above, in which target stimuli are briefly presented and then masked: Increased temporal certainty enhances perceptual sensitivity (*d*-prime) in both the foreperiod paradigm (Rolke, 2008; Rolke & Hofmann, 2007) and the temporal-cueing paradigm (Correa, Lupiáñez, & Tudela, 2005). However, although highly informative, these findings cannot adjudicate between effects on encoding and the rate of evidence accumulation (cf. Rolke & Hofmann, 2007). That is, perceptual sensitivity may be enhanced because encoding lasts shorter and evidence accumulation can start earlier, or because evidence accumulation progresses at a faster rate; both scenarios result in more evidence by the time the target stimulus is masked and subjects must make a decision. Bausenhart and colleagues have tried to distinguish between these accounts by investigating the foreperiod effect on the shape of speed-accuracy tradeoff functions obtained with the response-signal method (Bausenhart, Rolke, Seibold, & Ulrich, 2010). They found that foreperiod affected the intercept but not the slope of these functions, providing evidence for changes in encoding duration but not the rate of evidence accumulation. Together, these and other behavioral findings (Seifried, Ulrich, Bausenhart, Rolke, & Osman, 2010) provide substantial evidence that temporal certainty affects the duration of stimulus encoding.

While there is substantial evidence that temporal certainty affects the duration of encoding and motor processes, the picture is less clear for the two main components of the decision process: threshold setting and rate of evidence accumulation. According to the response-threshold account, increased temporal certainty results in a well-timed lowering of the response threshold, such that decisions are made on the basis of less evidence. A straightforward prediction of this account is that the faster RTs should be accompanied by a higher proportion of errors—choice errors in choice-RT tasks and false alarms in simple-RT tasks in catch trials. Unfortunately, studies with simple-RT tasks generally do not report false-alarm proportions, or do not include catch trials in the design. Furthermore, response accuracy in choice-RT tasks is generally near ceiling, which necessarily results in negligible and non-significant foreperiod effects. In the rare two-choice RT studies in which accuracy was off ceiling, foreperiod effects on accuracy were small or absent. An exception

is an experiment reported by Posner, Klein, Summers, and Buggie (1973), who found a speed-accuracy tradeoff when comparing foreperiods of 400 ms and 800 ms. A distinct feature of the results in this study were the extremely fast responses, due to speed emphasis in the task instructions. As we have discussed elsewhere (Jepma et al., 2009), the effect of lowering the decision threshold on the probability that the evidence-accumulation process reaches that threshold by mistake (i.e., resulting in an error), is larger when the threshold is closer to the starting point, as is the case when instructions emphasize speed. Thus, the increase in error rates with higher temporal certainty (foreperiod = 400 ms) in the experiment of Posner and colleagues is consistent with the response-threshold account and may have become apparent because of a small distance between starting point and threshold. Taken together, a review of speed-accuracy tradeoff data yields little evidence for or against the response-threshold account. Furthermore, as we will discuss later, although the response-threshold account predicts a speed-accuracy trade-off, the observation of a speed-accuracy trade-off is not uniquely diagnostic of shifts in response threshold.

Finally, as noted above, there is preliminary evidence that temporal certainty in the foreperiod paradigm does not affect the rate of evidence accumulation (Bausenhardt et al., 2010). Aside from those results, there are no data informing the evidence-accumulation account, in part because standard behavioral indices predicted by the evidence-accumulation account cannot be distinguished from predictions of the encoding account (cf. Rolke & Hofmann, 2007). Therefore, other methods are needed to test whether temporal certainty affects components of the decision process.

We conducted two experiments using the two paradigms that are most commonly used in temporal-certainty research: the fixed-foreperiod paradigm (Experiment 1) and the temporal-cueing paradigm (Experiment 2). Previous work has always focused on either the foreperiod paradigm or the temporal-cueing paradigm, which explains the lack of integration of the two literatures. To enable a comparison of the temporal-certainty effects in the two paradigms, we identified the psychological process(es) underlying the observed temporal-certainty effects in both paradigms using two sequential-sampling models for distributions of response times and error rates. One goal was to confirm the hypothesis that temporal certainty affects the duration of nondecision processes, as suggested by the literature reviewed above. However, the models we used were particularly useful for testing the evidence-accumulation and response-threshold accounts, because each of these components of decision making corresponds with a unique parameter in both models. Therefore, our primary goal was to examine whether the values of these decision-making parameters changed as a function of temporal certainty.

Experiment 1

In Experiment 1 we investigated which components of information processing are affected by temporal certainty using a diffusion-model analysis of the foreperiod effect on RT and accuracy. The diffusion model is a model of two-choice decision making that defines the decision process as

the continuous accumulation of noisy stimulus information over time, from a starting point towards one of two decision criteria or thresholds (Ratcliff & Rouder, 1998; see Figure 1). When one of the two thresholds is reached, the corresponding response is initiated. There are several reasons to assume that the diffusion model gives an accurate reflection of how the decision process is implemented in the brain. First, the diffusion process is the optimal decision process: it provides the fastest responses for a fixed level of accuracy, or the highest accuracy for a fixed response time (Wald, 1947). Second, the diffusion model explains the dynamics of neuronal activity during decision-making behavior (Gold & Shadlen, 2007; Smith & Ratcliff, 2004). And third, the diffusion model successfully accounts for RT distributions and error rates in a variety of two-alternative forced-choice tasks (e.g., Ratcliff, Van Zandt, & McKoon, 1999).

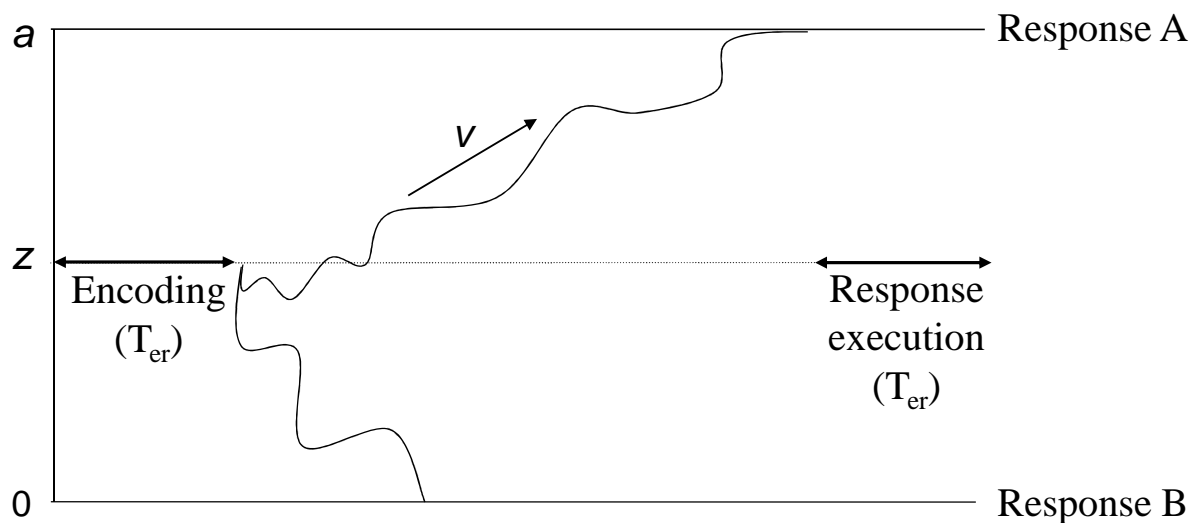


Figure 1. An illustration of the diffusion model. The parameters are: a = boundary separation, z = starting point, v = drift rate, T_{er} = mean nondesideration time. The sample paths represent moment-by-moment fluctuations in the evidence favoring the two possible responses, which is due to noise in the decision process. The decision process starts at z and terminates when one of the two boundaries is reached. The duration of T_{er} determines the additional time needed for stimulus encoding and response execution.

The diffusion model can be helpful in evaluating the various accounts of the foreperiod effect because some of the main model parameters correspond closely to the different processing components emphasized by these accounts. The three most important parameters of the model in this respect are the drift rate, the boundary separation, and the nondesideration component. The drift rate (v) is the mean rate of evidence accumulation in the decision process, which depends on the quality of the stimulus and the perceptual system. The higher the absolute value of the drift rate, the faster a decision threshold is reached. If accurate predictions of target onset time increase the drift rate of the diffusion model, this would support the idea that high temporal certainty induces a faster build-up of information. The boundary separation (a) is the distance between the two decision criteria. This parameter determines on how much evidence a decision is based, and can be controlled strategically by the decision maker. If the decision maker uses temporal prediction to briefly lower the boundary separation, this would provide support for the notion that the foreperiod

effect reflects a lowering of the decision threshold (Posner, 1978). Besides the decision process, there are other components of processing involved in a two-choice RT task, namely stimulus encoding and response execution which, respectively, precede and follow the decision process. In the diffusion model, these nondecision processes are combined into one nondecision component, T_{er} . A shortening of the nondecision component by accurate prediction of target onset would indicate that stimulus encoding and/or motor execution are speeded.

We applied the diffusion model to data from a standard lexical-decision task, in which participants were asked to classify letter strings as a word or a nonword, with task instructions emphasizing response speed in half of the blocks and response accuracy in the other half of the blocks. The diffusion model has been shown to provide a good fit of lexical-decision data, accounting for the effects of the experimental variables on RTs for correct and error responses, shapes of the RT distributions, and accuracy values (Ratcliff, Gomez, & McKoon, 2004; Wagenmakers, Ratcliff, Gomez, & McKoon, 2008). Importantly, each letter string was preceded by a warning signal, and the stimulus-onset asynchrony between the two stimuli, the foreperiod, was varied between blocks (500 or 2700 ms). Our major aim was to examine which model parameter(s) could best account for the corresponding differences in task performance.

Method

Participants. Fourteen students participated (11 women; aged 18-29 years; mean age = 21.5; all native Dutch speakers). All participants reported normal hearing and normal or corrected-to-normal vision. Each participant completed two sessions of approximately 90 minutes each, on separate days. Participants received either 18 euros or course credits for participation.

Design and procedure. Participants were tested individually in a dimly lit room. Stimuli were presented in silver on a navy blue background on a personal-computer screen. Each trial started with the presentation of a 200-ms asterisk symbol (visual angle = 0.8°) in the center of the screen, which marked the onset of the foreperiod. This warning signal was followed by the remainder of the foreperiod (300 ms or 2500 ms) during which a fixation plus (0.3°) was on the screen. Then a letter string was presented (Courier New font; visual angle = 2.7° for 4-letter words and 4.0° for 6-letter words), and participants were instructed to decide whether or not the letter string was a Dutch word by pressing the z or the / key. The key assignment was balanced across participants. The letter string remained on the screen until a response was made, after which the fixation plus reappeared for an intertrial interval of $(1.1 + X)$ s, with X being a random variable that followed an exponential distribution with a mean of 1 s. This random interval was used to emphasize the importance of the warning signal as a temporal reference for preparation (cf. Rolke & Hofmann, 2007).

The word stimuli were 800 Dutch words and 800 nonwords. Both the words and the nonwords consisted of 4, 5 or 6 letters (195 4-letter, 251 5-letter and 354 6-letter words as well as nonwords). The frequency of the words ranged from 0.07 to 5.48 per million (mean = 3.47, SD = 1.28; Baayen, Piepenbrock, & Gulikers, 1995). The nonwords were generated by replacing one

letter of an existing word; vowels were replaced by vowels and consonants by consonants. The words that were used to generate the nonwords were not used as word stimuli.

In each of the two sessions, participants completed two practice blocks of 24 trials, followed by 16 experimental blocks of 50 trials: 25 with a word and 25 with a nonword. The combination of speed-accuracy instructions and foreperiod changed after every two blocks according to an ABCD DCBA order that was the same in both sessions and varied across participants. Before the start of each block, participants received an on-screen announcement of the upcoming foreperiod (long or short) and speed-accuracy instructions (focus on accuracy or speed), after which they could press the space bar to start the block. In speed blocks, participants were instructed to respond as quickly as possible, but without making a lot of errors, and responses slower than 650 ms were followed by a message TOO SLOW of 1 s. When a response was faster than 250 ms, the message TOO FAST was displayed for 1 s. No accuracy feedback was given in these blocks. In accuracy blocks, participants were instructed to respond as accurately as possible, but without taking more time to respond than necessary, and incorrect responses were followed by a message ERROR of 1 s. Responses faster than 250 ms or slower than 1200 ms were followed by a TOO FAST or TOO SLOW message. At the end of each block the mean RT and the proportion of correct responses appeared on the screen, and participants could take a short break before initiating the next block.

Diffusion-model analysis. For fitting the diffusion model to the data we used the Diffusion Model Analysis Toolbox (DMAT; Vandekerckhove & Tuerlinckx, 2008). DMAT estimates parameters by maximizing a multinomial likelihood function. The data that are used to fit the diffusion model are the RT distributions for correct and incorrect responses, and the percentage correct responses.

We fitted four different diffusion models to the data. The following parameter settings applied to all models: 1) The intertrial variability in nondecision time (st) was held constant across all conditions. 2) The starting point of the diffusion process (z) was set at a fixed proportion of the boundary separation, such that the bias in starting point was constant across conditions. 3) Boundary separation (a) and the intertrial variability in starting point (sz) were free to vary between the speed and accuracy conditions (Ratcliff & Rouder, 1998, Experiment 1; Ratcliff, Thapar, & McKoon, 2001, Experiment 2). 4) Mean drift rate (v) and intertrial variability in drift rate (η) were free to vary between the word and nonword trials (Ratcliff, Thapar, Gomez, & McKoon, 2004). The four models differed with regard to the parameters that were free to vary as a function of foreperiod duration. In one model (the All free model), T_{er} , a , and v were all left free to vary. In addition, there were three models in which either T_{er} , a , or v could vary, whereas the other parameters were held constant (the T_{er} model, a model, and v model, respectively).

The models were fitted to the data in two ways. First, the models were fitted to each participant's data individually. When a participant made 10 or fewer errors in a condition, the participant's error data for this condition were not included in the fitting procedure. Second, the models were fitted to the averaged data. The averaged data was obtained by calculating the accuracy and the RTs for correct and error trials associated with the .1, .3, .5, .7 and .9 quantiles for

each individual participant, and then averaging these values across participants. (Note that the quantile RTs are not the mean RTs within bins [Ratcliff, 1979], but the boundary RTs of each quantile.)

Results

Behavioral results. Figure 2 shows the mean correct RT and mean percentage correct as a function of foreperiod duration, instruction and word type. RTs shorter than 250 ms or longer than 2500 ms were excluded from analysis, which resulted in the exclusion of 0.6% of the trials. In accordance with previous studies, RTs were shorter on short-foreperiod trials than on long-foreperiod trials (573 ms vs. 625 ms; $F(1,13) = 53.6, p < 0.001$), yielding a reliable foreperiod effect of 52 ms. Furthermore, RTs were shorter following speed instructions than following accuracy instructions (563 ms vs. 635 ms; $F(1,13) = 23.3, p < 0.001$), and shorter for words than for nonwords (584 ms vs. 615 ms; $F(1,13) = 10.6, p = 0.006$). There were no significant interactions between the three variables.

Percentage correct was lower on short-foreperiod trials than on long-foreperiod trials (80.7 vs. 82.4%, indicating that the increased speed on short-foreperiod trials was accompanied by a small but reliable drop in accuracy ($F(1,13) = 12.6, p = 0.004$). This drop in accuracy on short-foreperiod trials was present in the accuracy condition (83.9 vs. 87.2%) but not in the speed condition (77.6 vs. 77.7%), as reflected in a significant interaction between foreperiod duration and instruction, $F(1,13) = 8.2, p = 0.013$. As expected, percentage correct was higher when the instruction emphasized accuracy than when it emphasized speed (85.5% vs. 77.7%; $F(1,13) = 32.0, p < 0.001$).

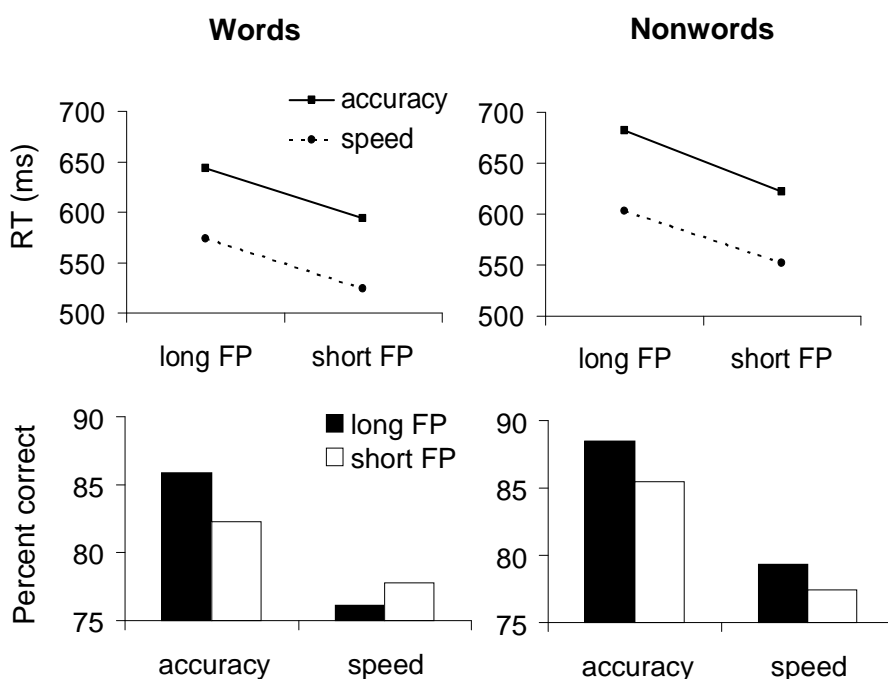


Figure 2. Mean correct RT and proportion correct in Experiment 1 as a function of word type, instruction (speed/accuracy) and foreperiod duration.

Experimental effects on the diffusion-model parameters. To assess which parameters were affected by foreperiod duration, we analyzed the foreperiod effect on the estimates of the T_{er} , a and v parameters in the All free model. Table 1 shows the average parameter estimates across participants. As expected, the boundary separation was smaller when the instruction emphasized speed than when it emphasized accuracy ($F(1,13) = 32.9, p < 0.001$). In addition, (absolute) drift rates were higher for words than for nonwords ($F(1,13) = 72.8, p < 0.001$). Importantly, neither boundary separation ($F(1,13) = 2.2, p = 0.16$) nor drift rate ($F(1,13) = 0.01, p = 0.91$) was affected by foreperiod. In contrast, the nondecision component, T_{er} , was significantly smaller on trials with a short foreperiod than on trials with a long foreperiod ($t(13) = 6.0, p < 0.001$). These results suggest that reducing temporal uncertainty shortens one or more nondecision processes, but does not substantially affect the decision process itself.

Table 1. Parameter estimates for the fit of the All free model (SD in parentheses) in Experiment 1. T_{er} = non-decision time (in seconds) comprising stimulus encoding and response execution; a = boundary separation; v = drift rate

parameter	Short FP	Long FP
T_{er}	.446 (.045)	.482 (.045)
a (speed)	.078 (.011)	.080 (.010)
a (accuracy)	.102 (.018)	.109 (.019)
v (words)	.295 (.139)	.314 (.171)
v (nonwords)	-.253 (.109)	-.269 (.108)

Model selection. To further assess the effect of foreperiod duration on the different model parameters, we tested which model had the best fit to the data. To compare the adequacy of the four models (i.e. the All free model, T_{er} model, a model, and v model) in explaining the observed data we used the Bayesian Information Criterion (BIC), a statistical criterion for model selection. The BIC is a decreasing function of the goodness-of-fit for the estimated model, and an increasing function of the number of free parameters to be estimated. Thus, the best model is the model with the lowest BIC value. In addition, the raw BIC values were transformed to a probability scale, enabling a more intuitive comparison of the probabilities of each model being the best model (Wagenmakers & Farrell, 2004). The transformation of BIC values to probability values consists of three steps. First, for each model i , the difference in BIC with respect to the model with the lowest BIC value is computed (i.e., $\Delta_i(\text{BIC})$). Second, the relative likelihood L of each model i is estimated by means of the following transformation: $L(M_i | \text{data}) \propto \exp[-0.5 \Delta_i(\text{BIC})]$, where \propto stands for “is proportional to”. Third, the model probabilities are computed by normalizing the relative model likelihoods, which is done by dividing each model likelihood by the sum of the likelihoods of all models. Table 2 summarizes the average BIC values and probabilities of each of the four models. The T_{er} model was by far the best model ($F(3,39) = 18.3, p < 0.001$). In the individual analyses, the T_{er} model was the best model for 10 of the 14 participants.

Since boundary separation (a) varied as a function of instruction, and drift rate (v) as a function of word type, the a model and v model had more free parameters (13) than the T_{er} model (12). To examine the possibility that the T_{er} model was favored because of its fewer free parameters, we fitted an additional a model to each participant's data in which the effects of instruction and foreperiod on a were additive instead of fully free. Similarly, we fitted an additional v model to each participant's data in which the effects of word type and foreperiod on v were additive. These additive a and v models had the same number of free parameters as the T_{er} model. The average BICs of the additive a and v models were somewhat larger but did not differ significantly from the fully-free versions of these models ($p = 0.21$ and $p = 0.98$ for the a and v models, respectively). Importantly, the additive a and v models had higher BICs than the T_{er} model ($ps < 0.01$), suggesting that the conclusion in favor of the T_{er} model was not due to the fewer free parameters of this model. For the sake of completeness we also examined the models in which combinations of two parameters (T_{er} and a ; T_{er} and v ; a and v) were free to vary as a function of foreperiod duration. The average BIC values of these three models were all higher than that of the T_{er} model, suggesting that the effects of temporal uncertainty could be explained best by a change in nondecision time alone.

Table 2. BIC values for each model in Experiment 1 (SD in parentheses).

	Df	BIC	$p(BIC)$
All free model	16	7,112 (492)	< 0.01
T_{er} model	12	7,102 (492)	> 0.99
a model	13	7,131 (491)	< 0.0001
v model	13	7,195 (512)	< 0.0001

Note: p = BIC model probability

Model fits. To examine the RT distributions, we averaged the .1, .3, .5, .7 and .9 quantile RTs across participants. Figure 3 shows the mean correct quantile RTs as well as the mean proportions correct in each condition. The predicted quantile RTs and proportions correct from the best model (the T_{er} model) are indicated as well. Figure 3 shows that all five quantile RTs of the correct responses were shorter on short-foreperiod trials than on long-foreperiod trials. However, the absolute foreperiod effect was small relative to the differences between the quantile RTs, which makes visual inspection difficult. To examine the foreperiod effect in more detail, we calculated the RT difference between short-foreperiod trials and long-foreperiod trials (i.e., the foreperiod effect) for each of the five correct RT quantiles. We then plotted the foreperiod effect as a function of response speed (the average of the quantile RTs in the long-foreperiod trials and short-foreperiod trials).

The resulting *delta plot* provides a way of zooming in on the foreperiod effect at different points of the RT distribution (e.g., Ridderinkhof, 2002). Figure 4 shows the delta plots for the observed data and for the data produced by the best-fitting T_{er} , a and v models. The foreperiod effect is rather constant across the .1 - .7 quantiles, as is predicted by the T_{er} model, but is somewhat

increased for the .9 quantile for the word conditions. The a and v models both predict that the foreperiod effect gradually increases as RTs become longer. Most of the conditions in the observed data did not show this pattern, which explains why the T_{er} provided a better account of the data than the a and v models.

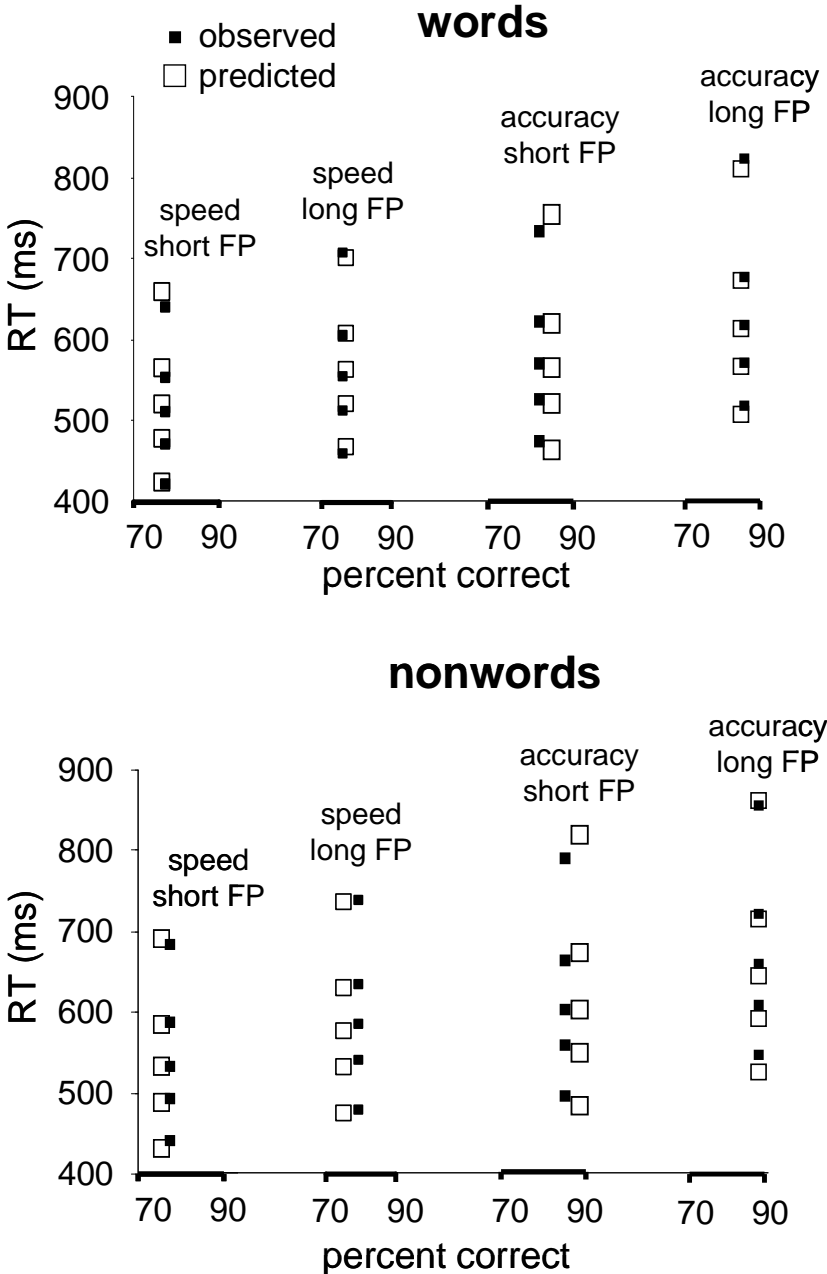


Figure 3. The observed and predicted (by T_{er} model) .1, .3, .5, .7 and .9 correct quantile RTs in Experiment 1, plotted against the corresponding proportions correct, as a function of word type, instruction (speed/accuracy) and foreperiod duration.

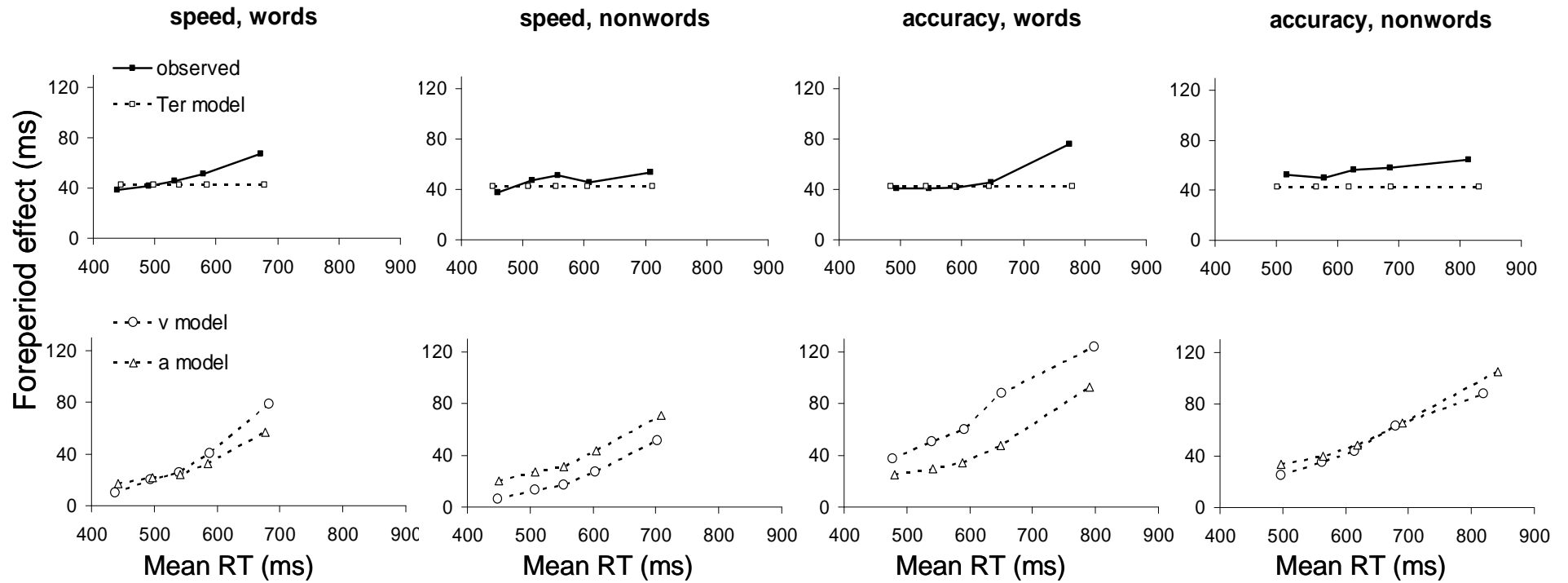


Figure 4. Observed and predicted delta plots showing the foreperiod effect on RT as a function of mean correct quantile RT, instruction (speed/accuracy) and word type in Experiment 1. The upper panels show the observed delta plots and the fit of the best model, the T_{er} model. The lower panels show the fits of the v model and the a model. Note that in the v model, the foreperiod effect varies with boundary separation a . This occurs because the changes in v have a larger impact on RT when a is large (accuracy instruction) than when a is small (speed instruction).

Discussion

We applied the diffusion model to the data from a lexical-decision experiment in which the visual imperative stimuli (letter strings) were preceded by a short or long foreperiod. The diffusion-model analysis of these data provided important evidence regarding the source of the foreperiod effect. The fit of a model in which all critical parameters were left unconstrained showed that the foreperiod effect was largely accounted for by a change in the nondecision component T_{er} . A comparison of models in which only one parameter was allowed to vary between short and long-foreperiod trials pointed in the same direction: for almost all of the participants the T_{er} model was best able to explain the data. The T_{er} model was also significantly better than a model in which all three parameters were free to vary as a function of foreperiod duration. Finally, consistent with previous studies (Hohle, 1965; Leth-Steensen, 2009), the foreperiod effect was relatively constant across the RT distribution. This implies that increased temporal certainty did not alter the shape of the RT distribution but shifted the complete distribution to the left, which is consistent with an effect on the nondecision component.

In contrast, the decision parameters drift rate and boundary separation, although sensitive to other experimental variables, were not substantially affected by foreperiod duration. In the behavioral analyses, we did find a potential indication for a foreperiod effect on boundary separation: there was a speed-accuracy trade-off between short and long-foreperiod trials when instructions emphasized accuracy, but not when instructions emphasized speed. As noted above, a speed-accuracy trade-off in the empirical data can provide a diagnostic criterion for a change in decision threshold. However, because this empirical pattern was not accompanied by a reliable foreperiod effect on the threshold model parameter, we propose another explanation of the speed-accuracy tradeoff. Laming (1979) has suggested that subjects may anticipate the arrival of a stimulus by starting sampling information from the perceptual display at the moment when they think the stimulus will be presented. If subjects start sampling too early, responses will be fast but also less accurate because they start with sampling noise. We assume that subjects use this strategy in blocks when the foreperiod is short and the anticipated timing of the stimulus is relatively good, but not in blocks with a fixed long foreperiod, when the stimulus onset is much harder to anticipate. In long-foreperiod blocks, subjects always wait with sampling until the target occurs, and errors due to premature sampling do not occur. According to this account, accuracy is reduced on short-foreperiod trials not because of a reduction in boundary separation but because subjects engage in premature sampling (of noise) on a proportion of the trials.

A prediction of the premature-sampling hypothesis in terms of diffusion-model parameters is that the inter-trial variability in starting point (sz) will be larger in short-foreperiod blocks than in long-foreperiod blocks, since premature sampling will inflate estimates of starting-point variability. To test this prediction, we fitted a diffusion model to the data in which not only boundary separation, drift rate and nondecision time, but also starting-point variability was free to vary as a function of foreperiod duration. This analysis revealed that estimated starting-point variability was significantly larger when instructions emphasized speed than when instructions emphasized

accuracy ($F(1,13) = 62.2, p < 0.001$). In addition, there was a trend-level effect of foreperiod duration ($F(1,13) = 3.72, p = 0.076$), as well as a significant interaction between foreperiod duration and instruction on estimated starting-point variability ($F(1,13) = 16.8, p = 0.001$)⁷. Follow-up contrasts indicated that starting-point variability was larger in short-foreperiod blocks than in long-foreperiod blocks when instructions emphasized accuracy (0.034 vs. 0.009; $t(13) = 3.14, p = 0.008$), but not when instructions emphasized speed (0.062 vs. 0.063; $t(13) = 0.21, p = 0.84$). Importantly, these effects of instruction and foreperiod on starting-point variability parallel the effects of instruction and foreperiod on behavioral accuracy (a drop in accuracy on short-foreperiod trials in the accuracy condition but not in the speed condition). These results support the idea that the observed speed-accuracy trade-off between short and long-foreperiod trials in the accuracy condition was due to premature sampling on a proportion of the short-foreperiod trials. Interestingly, this proportion of premature-sampling trials may also be responsible for a part of the observed decrease in the nondecision component T_{er} : on average, sampling (evidence accumulation) starts earlier on short-foreperiod trials than on long-foreperiod trials (when subjects always await the onset of the stimulus), resulting in a shorter encoding phase. However, this account cannot explain why perceptual sensitivity is improved on short-foreperiod trials (Correa et al., 2005; Rolke & Hofmann, 2007), indicating that there must be an additional, effective, shortening of encoding time.

The results from Experiment 1 strongly suggest that increased temporal certainty does not affect the decision process itself, but instead speeds up nondecision processes, consistent with our literature review. However, based on the diffusion-model analysis alone, it cannot be determined whether the shortening of the nondecision component reflects a speeding of stimulus encoding or response execution, or both.

Experiment 2

Besides the foreperiod paradigm, the effects of temporal expectation on task performance have been studied extensively with the temporal-cueing paradigm. In Experiment 2, we examined whether our conclusion that temporal certainty in the fixed-foreperiod paradigm affects mainly nondecision processes can be generalized to the temporal-cueing paradigm. The temporal-cueing paradigm is comparable to the variable-foreperiod paradigm in the sense that the foreperiod varies from trial to trial, but has the additional feature that the warning signal (cue) predicts the foreperiod duration with a large degree of certainty. In Experiment 2, these temporal cues were presented in the context of a simple-RT task, requiring rapid target detection; in choice-RT tasks temporal-cueing effects are generally absent, presumably because target discrimination interferes with the processing of the cue (Correa et al., 2004). On each trial, a cue predicted with a validity of 75% whether the cue-target interval was 400 or 1400 ms. Target brightness (bright or dim) was also

⁷ For this model, there were also significant effects of speed vs. accuracy instruction on boundary separation, of word type on drift rate, and of foreperiod duration on nondecision time.

varied between trials. We expected to find a cue-validity effect on RT for the short cue-target interval, because of differences in temporal preparation at the moment the target appears. A similar validity effect is generally not observed for the long cue-target interval (Correa et al., 2004; Coull & Nobre, 1998), because subjects have time to reorient their attention to the long cue-target interval after they realize that a cue indicating the short-cue interval is invalid (Correa et al., 2004; Karlin, 1959).

We analyzed the data using the shifted-Wald model (Wald, 1947; Figure 5), a model based on the Wald distribution, which represents the density of the first passage times of a Wiener diffusion process toward a single absorbing boundary. The shifted-Wald model conceptualizes the decision process as a single-boundary diffusion process, and successfully accounts for RT distributions in paradigms in which there is only a single response boundary, such as simple-RT tasks (Luce, 1986, pp. 51–57), go/no-go tasks (Heathcote, 2004; Schwarz, 2001; see Carpenter & Williams, 1995, for a comparable, ballistic approach).

This shifted-Wald distribution can be characterized by three parameters that correspond closely to the three main parameters of the diffusion model: the drift rate of the diffusion process (γ), the separation between the starting point of the diffusion process and the absorbing barrier (i.e. the decision threshold; α), and a parameter that shifts the entire RT distribution and thus quantifies the time needed for nondecision processes (θ).

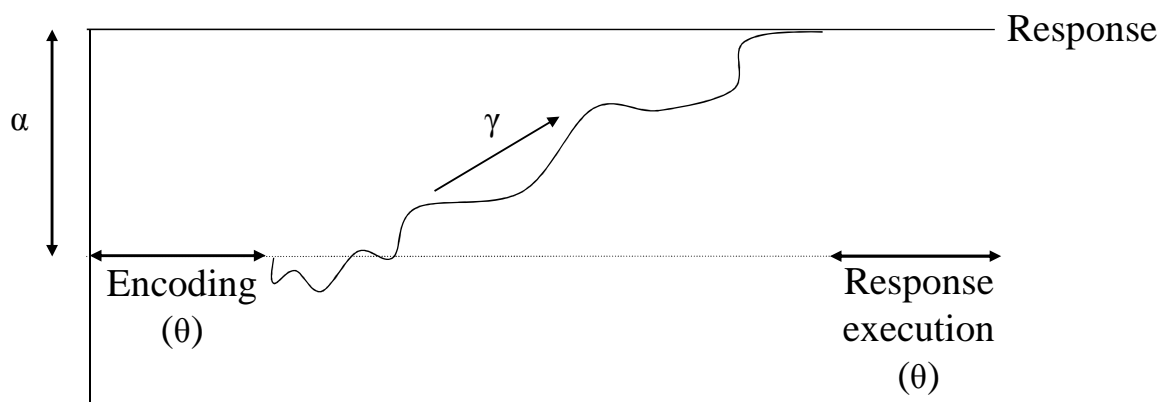


Figure 5. An illustration of the shifted-Wald model. The parameters are: a = distance between the starting point and the decision threshold, γ = drift rate, and θ = mean nondecision time.

Method

Participants. Sixteen students participated (14 women; aged 19-28 years; mean age = 21.8; all native Dutch speakers). Each participant completed one session of approximately 100 minutes in return for 13 euros or course credits.

Design and procedure. All stimuli were presented in the center of the screen on a black background. Each trial started with a white fixation point that was displayed for a quasi-random duration between 500-1500 ms (in steps of 200 ms). This was followed by the 50-ms presentation

of a grey, short (visual angle = $0.6^\circ \times 0.2^\circ$) or long ($1.4^\circ \times 0.2^\circ$) horizontal rectangular bar in the center of the screen. This cue provided information about the subsequent cue-target interval. Specifically, the short bar indicated that the target would appear early (i.e., cue-target interval = 400 ms) on 75% of the trials (valid cue) and late (cue-target interval = 1400 ms) on 25% of the trials (invalid cue). The long bar indicated that the target would appear late (cue-target interval = 1400 ms) on 75% of the trials (valid cue) and early (cue-target interval = 400 ms) on 25% of the trials (invalid cue). The cue was followed by a blank screen for the remainder of the cue-target interval (350 ms or 1300 ms). Then the target, a white (bright) or dark grey (dim) circle (visual angle = 1.0°) was presented for 100 ms, followed by a blank screen until the participant made a response. Then the next trial began. When no response was registered within 2 s of target onset, the message “You have not responded” was presented for 1 s. If a response with $RT < 100$ ms was registered, the message “Too fast! Wait with responding until the circle appears” was presented for 2 s.

Before the start of the experiment, participants were dark-adapted for 5 min in a room sealed from light. Dark adaptation increases the difference in RTs between bright and near-threshold stimuli (cf. Jaśkowski, Kurczewska, Nowik, van der Lubbe, & Verleger, 2007). The actual experiment started with 16 practice trials, followed by 16 blocks of 112 trials. Each block contained 28 trials with each combination of cue-target interval (short, long) and target brightness (bright, dim), 7 (25%) of which were invalidly cued. There was a 1-minute break between blocks and a 5-minute break halfway through the experiment. Participants were instructed to press the space bar as soon as they detected the target. They were encouraged to use the cue to optimize performance. At the end of each block the mean RT and the proportion of correct responses (= non-anticipations) appeared on the screen.

Shifted-Wald-model analysis. To assess the processing components that are affected by temporal uncertainty, the parameters γ , α , and θ were left free to vary as a function of cue validity and cue-target interval. In addition, the parameters γ and θ were free to vary as a function of target brightness, but α was not, reflecting the notion that subjects cannot instantaneously adjust the decision threshold once the (dim or bright) target is presented.

To reduce the impact of a few very short and long reaction times on the parameter estimates, we fitted to the data a mixture of the shifted-Wald distribution and a uniform distribution of response contaminants (e.g., Ratcliff & Tuerlinckx, 2002; Zeigenfuse & Lee, 2010). The uniform distribution of contaminants ranged from 100 ms to 1000 ms – the RTs below and above these boundaries were excluded from analysis.

Participant heterogeneity in the parameter estimates for the mixture-shifted-Wald model was taken into account using hierarchical Bayesian modeling (e.g., Farrell & Ludwig, 2008; Gelman & Hill, 2007; Rouder, Lu, Speckman, Sun, & Jiang, 2005; Rouder, Sun, Speckman, Lu, & Zhou, 2003; Shiffrin, Lee, Kim, & Wagenmakers, 2008). Hierarchical Bayesian methods reduce the variability in the recovered parameters and produce more accurate parameter estimates than single-level maximum likelihood estimation (Farrell & Ludwig, 2008; Rouder et al., 2005). The hierarchical Bayesian approach assumes that the parameters of individual participants are drawn

from group-level distributions that specify how the individual parameters are distributed in the population. The group-level distributions thus define the between-subjects variations of the parameters and can themselves be characterized by a set of parameters. One of the benefits of hierarchical modeling is that knowledge from the group-level distribution serves to shrink noisy estimates for individual participants to less extreme values.

In the Bayesian hierarchical model, individual parameters γ_i , α_i , θ_i –for the shifted-Wald distribution– and π_i –the mixture proportion– are assumed to come from group-level distributions with means μ_γ , μ_α , μ_θ and μ_π . These distributions were assumed to be normal, both for the shifted-Wald parameters and for the probit-transformed mixture proportion. The mean and standard deviation of the group-level distributions needed to be assigned prior distributions; these distributions were uninformative in the sense that the posterior distributions were not noticeably influenced by increasing or decreasing the width of the prior distributions⁸.

Parameter estimation for the mixture-shifted-Wald model was carried out by means of Markov chain Monte Carlo (MCMC) sampling in the WinBUGS program (Lunn, Thomas, Best, & Spiegelhalter, 2000; Lunn, Spiegelhalter, Thomas, & Best, 2009). The WinBUGS code that was used to fit the model can be found at www.ejwagenmakers.com. For reasons of speed and robustness, the likelihood function for the mixture between uniform and shifted-Wald distributions was coded separately and made available via the WinBUGS Development Interface (WBDev; e.g., Wetzels, Lee, & Wagenmakers, 2010). The MCMC sampling used three separate chains; each chain had a burn-in of 20,000 iterations, after which 20,000 further samples were drawn with a thinning factor of 10. This left 2,000 samples per chain for a total of 6,000 samples for each posterior distribution. Visual inspection and calculation of the R-hat statistic (Gelman & Rubin, 1992) confirmed that the three chains had converged to the same distribution (i.e., for all group-level parameters, R-hat = 1.00).

The results showed that the probability of a response contaminant was very low; for the group-level mean parameter, the mode of the posterior distribution was only .004. Nevertheless, inclusion of the contaminant distribution had a pronounced effect on the estimated nondecision time θ – without the contaminant distribution, θ was estimated to be implausibly low. Note that in the absence of a contaminant distribution, the entire distribution of θ has to be lower than the minimum observed RT. Thus, the inclusion of the contaminant distribution made the model more robust to misspecification due to the presence of outliers, even though the probability of observing an outlier was very low.

⁸ Because of numerical underflow errors for the likelihood, the Wald distribution does not allow one to use completely uninformative prior distributions. For this reason, we used prior distributions that were uninformative within a range that is plausible for data from a simple-RT task. See www.ejwagenmakers.com for a precise specification of the prior distribution, the model code, and the model output.

Results

Behavioral results. RTs shorter than 100 ms and longer than 1000 ms were excluded from analysis, which resulted in the exclusion of 1.8% of the trials. The proportion of trials on which participants failed to respond was 0.6% (<1.5% misses for all participants). The number of misses was larger on invalid than on valid trials, $F(1,15)=2.3$, $p=.002$. Figure 6 shows mean RT as a function of cue-target interval, cue validity, and target brightness. RTs were faster for bright targets than for dim targets (282 ms vs. 351 ms; $F(1,15) = 274.6$, $p < 0.001$); and faster for the long cue-target interval than for the short cue-target interval (307 ms vs. 326 ms; $F(1,15) = 13.2$, $p = 0.002$). Furthermore, as expected, RTs were faster on validly cued than on invalidly cued trials (308 ms vs. 324 ms; $F(1,15) = 29.5$, $p < 0.001$), indicating that participants used the cues to optimize their performance. As expected, the effect of cue validity was much larger for the short cue-target interval (28 ms) than for the long cue-target interval (6 ms; $F(1,15) = 12.2$, $p = 0.003$). This 2-way interaction effect was qualified by a significant 3-way interaction ($F(1,15) = 13.6$, $p = 0.002$), indicating that the cue-validity effect was the largest when the cue-target interval was short (i.e. when participants could not reorient their attention on invalidly cued trials) and the target was dim (i.e. when there was room for improvement in RT performance).

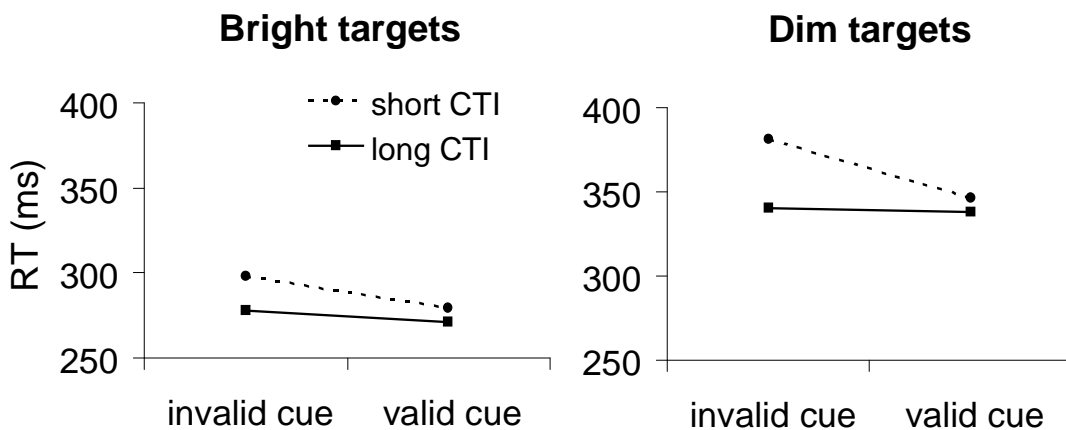


Figure 6. Mean RT in Experiment 2 as a function of cue-target interval (CTI), cue validity, and target brightness (bright, dim).

Experimental effects on the shifted-Wald model parameters. The results for the parameters of substantive interest are shown in Table 3. As expected, drift rate γ was higher for bright than for dim targets, $F(1,15) = 76.91$, $p < 0.001$, but was not affected by cue-target interval and cue validity ($ps > 0.8$). Decision threshold α tended to be lower for the long cue-target interval than for the short cue-target interval, $F(1,15) = 3.711$, $p = 0.07$. Importantly, cue validity only affected the nondecision component θ . The θ parameter was significantly smaller on validly cued trials than on invalidly cued trials, $F(1,15) = 7.7$, $p = 0.01$. Furthermore, there was an interaction between cue validity and cue-target interval, $F(1,15) = 24.4$, $p < 0.001$, indicating that the validity effect on θ was present on trials with a short cue-target interval (mean = 24 ms) but not on trials with a long

cue-target interval (mean = -3 ms), mimicking the validity effects on RT (28 ms and 6 ms, respectively). Finally, θ was smaller for bright targets than dim targets, $F(1,15) = 32.6$, $p < 0.001$.

Table 3. Parameter estimates for the fit of the mixture-shifted-Wald model in Experiment 2. The upper half of the table reports the averages of the individual parameter values (SD in parentheses), and the lower half of the table reports the posterior means of the group-level normal distributions from which the individual parameters were drawn. θ = non-decision time (in seconds) comprising stimulus encoding and response execution; α = decision threshold; γ = drift rate.

		Short cue-target interval		Long cue-target interval	
Parameter		Invalid cue	Valid cue	Invalid cue	Valid cue
Averages of the individual parameter values	θ (dim)	.156 (.153)	.131 (.066)	.152 (.068)	.156 (.075)
	θ (bright)	.118 (.036)	.095 (.050)	.122 (.040)	0.123 (.054)
	γ (dim)	6.26 (1.12)	6.44 (1.50)	6.40 (1.31)	6.31 (1.10)
	γ (bright)	8.01 (1.84)	7.58 (1.61)	7.79 (2.06)	8.01 (1.85)
	α	1.37 (.26)	1.34 (.26)	1.17 (.34)	1.14 (.34)
Means of the group-level parameter distributions	μ_θ (dim)	.156 (.016)	.132 (.019)	.152 (.020)	.156 (.021)
	μ_θ (bright)	.118 (.011)	.095 (.015)	.123 (.012)	.124 (.015)
	μ_γ (dim)	6.28 (.35)	6.47 (.43)	6.44 (.41)	6.33 (.33)
	μ_γ (bright)	8.01 (.55)	7.59 (.47)	7.81 (.59)	8.01 (.53)
	μ_α	1.37 (0.09)	1.34 (.09)	1.17 (0.11)	1.14 (.10)

Note: dim = dim target; bright = bright target

Model fit. Figure 7 shows the mean observed .1, .3, .5, .7 and .9 quantile RTs in each condition, as well as those predicted by the shifted-Wald model. The model provided a generally good fit to the empirical RT quantiles; the largest difference between the observed and model-predicted quantile RTs was 15 ms, and the average difference was 6 ms. For the short cue-target interval, all five quantile RTs associated with bright and dim targets were shorter on validly cued trials than on invalidly cued trials. This cue-validity effect was less pronounced or absent for the long cue-target interval. To examine in more detail the cue-validity effect at different points of the RT distribution, we plotted the observed and predicted cue-validity effect for each of the five RT quantiles as a function of response speed (the average of the quantile RTs in the validly cued trials and invalidly cued trials). The resulting delta plots are shown in Figure 8. For the bright targets, the cue-validity effect at the short cue-target interval was rather constant across the five RT quantiles, which suggests that cue validity mainly affected the nondecision time (i.e., parameter θ of the shifted-Wald model). For the dim targets, however, the cue-validity effect at the short cue-target interval increased with increasing RTs. To assess whether this increase was significant, we subjected the cue-validity effect at each quantile to a linear-regression analysis with mean quantile RT and a constant as explanatory factors, separately for each participant (Burle, van den Wildenberg, & Ridderinkhof, 2005; De Jong, Liang, & Lauber, 1994). We then tested whether the average regression coefficient of mean quantile RT (i.e., the slope of the delta plot) was

significantly different from 0, using a one-sample t -test. This test just reached significance (mean regression coefficient = 0.12; SD = 0.21; $t(15) = 2.2$, $p = 0.044$), suggesting that, for the dim targets, part of the cue-validity effect was attributable to an effect on the decision process. Because target brightness was varied on a trial-by-trial basis, processing of bright and dim targets could differ in drift rate but not in decision threshold. Therefore, the increasing validity effect with increasing RT for the dim targets was likely due to a cue-validity effect on drift rate (i.e., parameter γ of the shifted-Wald model).

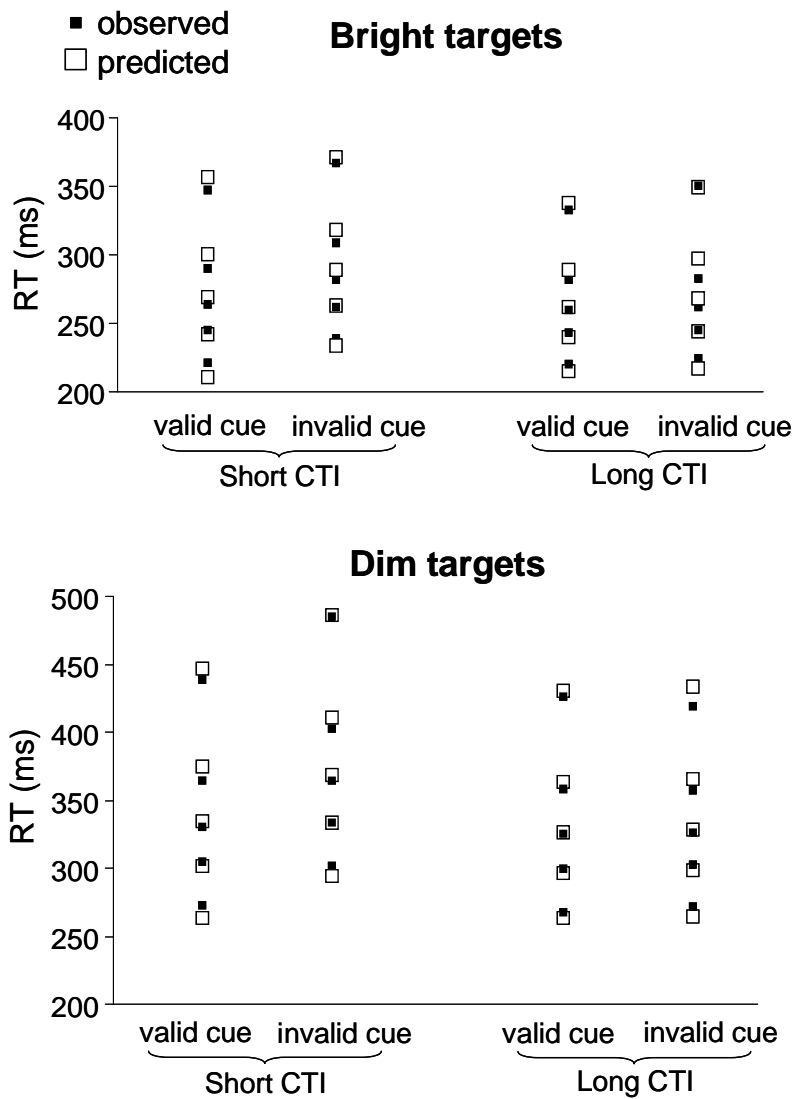


Figure 7. The observed and predicted .1, .3, .5, .7 and .9 quantile RTs in Experiment 2 as a function of target brightness (bright, dim), cue-target interval (CTI) and cue validity.

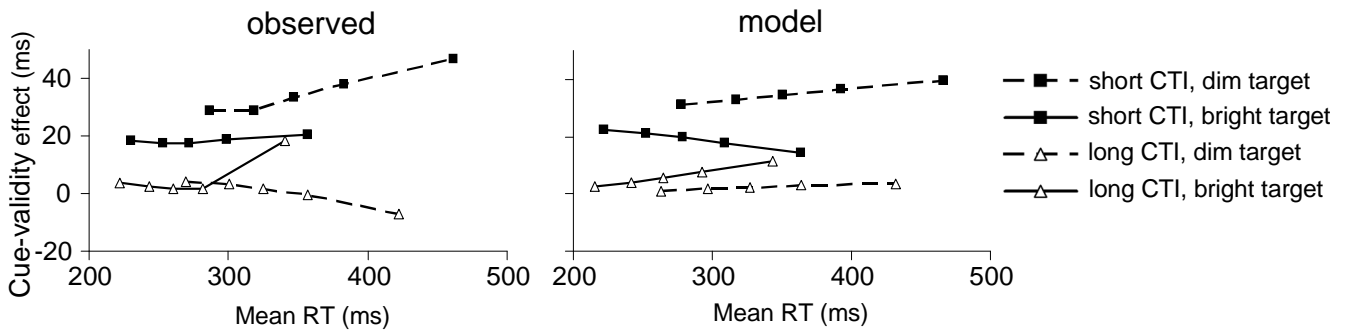


Figure 8. Observed and predicted delta plots showing the cue-Validity effect on RT as a function of mean quantile RT, cue-target interval (CTI) and target brightness (bright, dim) in Experiment 2.

Discussion

We applied the shifted-Wald model to the data from a simple-RT experiment in which the targets were preceded by a cue that validly or invalidly indicated the cue-target interval: short (400 ms) or long (1400 ms). As expected we found a substantial cue-Validity effect on RT for the short cue-target interval but not for the long cue-target interval, because the participants had time to reorient their attention to the long cue-target interval after they realized that a cue indicating the short-cue interval was invalid (Correa et al., 2004; Karlin, 1959). The model analysis provided useful evidence regarding the source of the cue-Validity effect: Cue validity significantly affected the θ parameter, but not the parameters of the decision process, γ and α . Indeed, the effects of cue validity on the estimated duration of nondecision processes were very similar in size to the cue-Validity effects on RT, both at the short and the long cue-target interval. The delta plots showed a somewhat more complicated pattern: in one condition (short cue-target interval, bright targets) the cue-Validity effect was relatively constant across the RT distribution, suggesting that increased temporal certainty decreased the duration of the nondecision component. In another condition (short cue-target interval, dim targets) the cue-Validity effect showed an increase across RT bins, suggesting that increased temporal certainty increased the rate of evidence accumulation. However, the absence of an effect of cue validity on the γ parameter, and the nonsignificant interactions between cue validity and the other variables on γ , suggest that this effect was relatively minor. Thus, the cue-Validity effect was largely accounted for by a change in the nondecision component θ .

Another interesting finding in Experiment 2 was the trend-level effect of cue-target interval on estimated decision threshold (parameter α ; $p = .07$): the decision threshold was lower for the long cue-target interval than for the short cue-target interval. At first blush, this finding seems inconsistent with the absence of an effect of foreperiod on boundary separation in Experiment 1. But on closer thought, the two experiments are rather different in terms of the effect of warning interval. In the simple-RT task of Experiment 2, participants could substantially lower the decision threshold if the target had not appeared after the short cue-target interval: there was no more uncertainty about the timing of the target, the long cue-target interval was relatively short (1400 ms)

and hence easier to anticipate, and the identity of the response was known. Accordingly, in Experiment 2 participants responded faster when the cue-target interval was long compared to when it was short. Conversely, in the choice-RT task of Experiment 1, the long foreperiod was relatively long (2700 ms) and hence harder to anticipate, and there was always the risk of making choice errors if the boundary separation was set too small. Accordingly, in this experiment participants responded slower when the foreperiod was long compared to when it was short. Therefore, the effects of warning interval on temporal certainty went in opposite directions in the two experiments, which mirrors the opposing effects of long and short foreperiods on temporal certainty in fixed and variable-foreperiod paradigms (Bertelson, & Tisseyre, 1968; Vallesi, McIntosh, & Stuss, 2009).

General Discussion

Preparing the system to respond to an upcoming stimulus is energy-consuming and maintaining such a state of readiness, because stimulus onset time is uncertain, can be experienced as an aversive state (Gottsdanker, 1975; Näätänen, 1972). This indicates the importance of using cues to predict stimulus onset and time the system's preparation accordingly. We conducted two experiments, using the foreperiod paradigm (Experiment 1) and the temporal-cueing paradigm (Experiment 2), to assess which components of information processing are speeded when subjects use such temporal cues to reduce uncertainty. The results from these two experiments were consistent: temporal certainty affected the duration of nondecision processes but had little effect on the two critical components of the decision process—decision-threshold setting and the rate of evidence accumulation.

Our findings are consistent with two previous studies that examined correct-RT distributions (Leth-Steensen, 2009) and speed-accuracy tradeoff functions (Bausenhart, et al., 2010) in the foreperiod paradigm, and found that manipulations of foreperiod mainly shifted these distributions while having very little effect on their shapes. The novel contributions of our study are that we analyzed temporal certainty effects in both the foreperiod paradigm and the temporal-cueing paradigm, using sequential-sampling models of decision making that took into account response accuracy and RT distributions on correct and error trials. Our findings therefore provide the strongest evidence to date that temporal certainty effects on simple-RT and choice-RT reflect a change in the duration of nondecision processes, not changes in the decision process.

Although our results cannot distinguish between effects of temporal certainty on encoding and motor processes, the literature suggests that the duration of both types of processes is affected. Temporal certainty modulates many aspects of perception (Nobre et al., 2007), including perceptual sensitivity in the foreperiod paradigm and temporal-cueing paradigm (Correa et al., 2005; Rolke, 2008; Rolke & Hofmann, 2007), and the duration of perceptual processing in a clock paradigm (Seifried et al., 2010). Temporal certainty also modulates various aspects of motor preparation (Davranche et al. 2007; Miniussi, Wilding, Coull, & Nobre, 1999; Riehle et al., 1997) and decreases the duration of motor preparation and execution, although effect sizes are small (Tandonnet et al.,

2003, 2006). Näätänen's (1971) model suggests that subjects may use temporal cues to anticipate the arrival of the imperative stimulus by increasing the level of 'motor readiness', such that the time to reach the 'motor action limit' is reduced⁹. This model is supported by findings that increased temporal certainty reduces the force generated to execute the response (Mattes & Ulrich, 1997) and the activation of the corresponding primary motor cortex (Tandonnet et al., 2006).

Our conclusions stand in sharp contrast with those reached by Hackley (2009) on the basis of a review of ERP studies with the foreperiod paradigm. Hackley's main argument against an encoding account is that temporal certainty has little or no effect on the latency of the P1 and N1, two early perceptual brain potentials (reviewed in Correa et al. 2006; see Hackley et al., 2007 for a significant but very small effect), and the latency of the N2pc (Hackley et al., 2007), an electrophysiological index of the allocation of spatial attention. A possible explanation of these findings is that the latency of early ERP components is not a reliable index of the duration of task-relevant encoding processes. For example, because of the parallel organization of the visual system, the processes underlying these ERP components may not lie in the pathway that determines the RT. Hackley et al. (2007) reject this hypothesis with the argument that N2pc latency has been found to correlate highly with RT in a number of studies. However, a problem with this argument is that these N2pc-RT correlations were found in experiments with an important spatial component (i.e., requiring the N2pc process to perform the task), whereas the non-significant effect of foreperiod on N2pc latency was found in a study in which stimulus location played a negligible role (Hackley et al., 2007). Another possible explanation, suggested by Hackley (2009), is that increased temporal certainty leads to increased visual-cortex activation in response to the visual imperative stimulus, as reflected in increased P1 and N1 amplitudes (i.e., a nonchronometric change), changes that then propagate forward to produce a greater speed of subsequent encoding processes. This proposal is consistent with P1/N1 amplitude effects of temporal certainty (Correa et al., 2006) and with our recent proposal regarding the temporal locus of the accessory stimulus effect (Jepma et al., 2009).

Hackley's (2009) argument against the motor preparation account is that foreperiod duration has little or no effect on the interval between LRP onset and the overt response (e.g., Hackley et al., 2007; Müller-Gethmann, Ulrich, & Rinckenauer, 2003). However, a limitation of the LRP double-subtraction measure is that it is blind to the respective contributions of each individual motor cortex. To address this limitation, Tandonnet et al. (2003, 2006) used Laplacian-transformed ERP waveforms to obtain separate estimates of the ipsilateral and contralateral motor cortex response, and found that increased temporal certainty decreased the duration of motor preparation of the responding hand (by 25 ms and 18 ms in the 2003- and 2006-studies, respectively). Because the same data showed no reliable effect of foreperiod on the (Laplacian and monopolar) LRP-to-response interval, Tandonnet and colleagues suggested that the effect of interest (i.e., timing of preparation of the responding hand) may be masked in the LRP by preparatory effects on activation in the ipsilateral, non-involved motor cortex. It is unclear whether similar subtle latency effects

⁹ This change in the distance to the motor threshold, which is not modeled in the sequential-sampling models used here, must be distinguished from response-threshold changes in the decision process.

were also present in the constituent ERP waveforms in the LRP studies reviewed by Hackley (2009). In any case, future ERP research needs to resolve the issue of how the onset of motor preparation processes should be measured.

Our conclusion that temporal certainty has little effect on the decision threshold might appear incompatible with occasional findings (including in Experiment 1) that temporal certainty causes a speed-accuracy tradeoff, a phenomenon that has been taken as diagnostic of decision-threshold modulations. However, on the basis of results in Experiment 1, we have suggested that a speed-accuracy tradeoff can be explained by an alternative hypothesis: when temporal certainty is high and the moment of stimulus onset is relatively easy to anticipate, subjects may engage in premature sampling of stimulus information on a proportion of the trials. Such premature sampling will lead to faster but less accurate responses because subjects will start with sampling noise. Thus, behavioral speed-accuracy trade-offs may be explained not only by changes in decision threshold but also by changes in premature sampling, which is an interesting topic for future research.

Our results provide important clues about the components of information processing that are speeded when people use temporal cues to anticipate the onset of an imperative stimulus. But ultimately we also need to understand the neural mechanisms underlying this voluntary control of temporal expectation. Neuroimaging and patient studies have suggested an important role for prefrontal structures in controlling temporal expectation in the foreperiod paradigm (Hackley et al., 2009) and the temporal-cueing paradigm (Coull & Nobre, 1998; Triviño, Correa, Arnedo, & Lupiáñez, 2010). Other studies have identified norepinephrine as a key neuromodulator underlying temporal certainty effects (Coull, Nobre, & Frith, 2001; Witte & Marrocco, 1997), consistent with the finding that the firing rate of locus coeruleus neurons increases during the warning interval in the foreperiod paradigm (Yamamoto & Ozawa, 1989). It will be a challenge for future studies to determine the exact mechanisms by which prefrontal structures and/or the locus coeruleus-norepinephrine system control the duration of nondecision processes as a function of degree of temporal expectation.