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Time-Based Expectancy in Temporally Structured Task Switching

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In many situations, people have to switch between different tasks. Previous research has shown that task switching leads to relatively slow responses and high error rates. In many real-life task-switching contexts, tasks are not randomly distributed over time, but the temporal distribution of tasks carries information. Often the delay before a task predicts to some degree which task it will be, like when a longer browser loading time for a website makes the search for an alternative more likely. The present study investigated whether and how humans adapt to such temporal regularities. In a series of five experiments, intertask delays predicted with different probabilities the task in the upcoming trial, or whether the task switches in the upcoming trial. Participants adapted their response behavior to the predictability of the task, for all tested degrees of predictability (70%, 80%, 90%), but only for the degree of 90% predictability when the task transition was temporally predictable. The adaptation was implicit and task repetitions as well as switches, both benefitted from this adaptation. Likewise, performance after 500 ms and 1,500 ms delays was facilitated by time-based predictability. The results are discussed in the context of previous findings on nontemporal task predictability.

Public Significance Statement
In real-life multitasking scenarios, the time people have to wait for a task is often predictive concerning the type of task which is required to be done next. We show in several experiments that humans adapt to such time-based task predictability, without becoming aware of the predictive value of the interval duration. These findings have important implications for the scheduling of system delays in human-machine interaction.

Keywords: task switching, executive control, timing, preparation

Multitasking is a phenomenon prevalent to our modern constantly accelerating life. Cognitive researchers commonly separate multitasking into situations where several tasks have to be executed concurrently (dual tasking; see Pashler, 1994), and situations in which one has to sequentially switch and execute different tasks in succession. The latter phenomenon is called *task switching* and is the focus of the present study (e.g., Kiesel et al., 2010). Timing has turned out to be a key factor in task switching. For example, empirical evidence concerning task preparation and interference between tasks comes primarily from studies which manipulated the duration of the time interval prior to stimulus onset (see Kiesel et al., 2010). The main finding is that increasing the temporal delay between tasks usually reduces interference from the previous task and supports preparation for the next task (see Kiesel et al., 2010; Pashler, 1998; Vandierendonck, Liefooghe, & Verbruggen, 2010).

In many real-life task-switching situations, this temporal delay between tasks is highly predictive with regard to the next task. For example, the duration of the system response delay after clicking on a web-link is highly informative about which task will be required next. During the first seconds of the delay, it is likely that the page will load successfully, requiring one to navigate on the page. When, on the contrary, the delay takes longer, it becomes increasingly likely that an error message occurs instead, requiring one to search for another link (Thomaschke, Kunchulia, & Dreisbach, 2015). This time-based task predictability is likely to have a strong impact on cognitive processing and behavior in task

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switching. Earlier studies, which used explicit or implicit task sequences or explicit task cues have shown that the cognitive system uses task predictability for task preparation, thereby substantially improving task performance (see Kiesel et al., 2010; Ruge, Jamadar, Zimmermann, & Karayanidis, 2013, for reviews; Wendt, Luna-Rodriguez, Reisenauer, Jacobsen, & Dreisbach, 2012). It is surprising that the effects of *time-based* task predictability have, however, not yet been investigated. By using different degrees of predictability, Experiments 1 through 3 will therefore investigate whether tasks can be expected based on time in a task-switching scenario.

Previous studies have also shown that anticipatory cognitive control seems to enhance preparation not only for specific task sets, but also for task transition (i.e., task switches and task repetitions) in single trials (Dreisbach & Haider, 2006; Farooqui & Manly, 2015). Therefore, Experiments 4 and 5 will investigate whether time-based predictability can be also used to expect task transitions in the task-switching paradigm.

Nontemporal Task Predictability

Previous research has shown that performance deficits associated with task-switching environments can be substantially reduced, when the upcoming task is predictable. The effects of task predictability have been extensively investigated during the last couple of decades (Gotler, Meiran, & Tzelgov, 2003; Koch, 2005; Meiran, 1996; Rogers & Monsell, 1995) by employing a variety of different paradigms. These paradigms differ, among other aspects, in the source of predictability. While numerous studies have investigated the effect of task predictability by providing explicit task cues preceding the imperative target stimuli (e.g., Dreisbach, Haider, & Kluwe, 2002; Hoffmann, Kiesel, & Sebald, 2003; Koch & Allport, 2006; Meiran, 1996; Meiran, Chorev, & Sapir, 2000; Ruge et al., 2005; Sudevan & Taylor, 1987), predictability comes from the task sequence itself in other studies. One of the most widely applied paradigms with simple predictable task sequences is the alternating-runs paradigm, introduced by Rogers and Monsell (1995). Task predictability, induced in this way, has a robust beneficial effect on performance, relative to random task-switching (see Koch, 2005, for a review).

Whereas the sequence is short and obvious in the alternating-runs paradigm, other studies have shown that there is also a sequence-based task predictability benefit, when the sequence is more complex and unknown to participants. Gotler and colleagues (2003), for example, used an eight-trial sequence of two different tasks, which were each indicated by an instruction cue. Although participants were not informed about the predictable sequences during the experiment, performance decreased when participants were transferred to a random sequence (see also Heuer, Schmidtke, & Kleinsorge, 2001; Weiermann, Cock, & Meier, 2010). Thus, sequence-based predictability facilitates performance, even when participants are not aware of the sequence.

However, in many everyday life interaction environments, the cue for a task is not a specific event, but it is instead implicitly in the flow of time. The duration of a delay before a task requirement often predicts which task will be required (remember the aforementioned example from the field of human machine interaction, where the duration of the system response delay after clicking on a web-link predicts to a high degree which task will be required next).

Time-Based Predictability

While time-based predictability of tasks has not yet been investigated until now, there is currently a fast-growing number of studies on time-based predictability of other event aspects (see Thomaschke & Dreisbach, 2015, for a review). Two previous studies have shown that time-based predictability of responses leads to faster responses for validly than for invalidly predicted responses (Thomaschke & Dreisbach, 2013; Thomaschke, Kiesel, & Hoffmann, 2011). A study by Wendt and Kiesel (2011) found that time-based predictability of conflict likelihood modulated conflict adjustment in the flanker task. Further related studies have investigated the time-based predictability of word valence (Roberts, Margutti, & Takano, 2011; Thomaschke, Bogon, & Dreisbach, submitted), linguistic complexity (Watanabe, Hirose, Den, & Minematsu, 2008), and stimulus location (Rieth & Huber, 2013). Moreover, it could be shown that computer users seem to predict upcoming events on the basis of preceding system response delays (Thomaschke & Haering, 2014). However, as all these studies employed single-task scenarios, time-based predictability of complex tasks has not previously been manipulated.

Time-based predictability is typically investigated by applying a specific variant of the foreperiod paradigm (Schröter, Birngruber, Bratzke, Miller, & Ulrich, 2015), namely the time-event correlation paradigm, which was initially introduced by Wagener and Hoffmann (2010). In this paradigm, participants perform a choice response to a target stimulus, which is preceded by a marked warning interval. This warning interval can have two possible durations. Both durations occur at any trial with equal probability. However, one aspect of the target stimulus is correlated with the interval duration. This aspect can, for example, be the required response. This would mean that, after the short interval, one of the two possible responses is more likely, and after the long interval, the other response is more likely (e.g., Thomaschke & Dreisbach, 2013). Thus, on the basis of the preceding interval, the aspect of the target (in this example, the response) is predictable. Participants typically respond faster and are less error-prone on trials with valid time-based predictability, compared to trials with invalid time-based predictability. This pattern is referred to as a *time-based predictability effect* (Thomaschke et al., 2015).

The time-based predictability effect is commonly explained by time-based expectancy (Wagener & Hoffmann, 2010; Wendt & Kiesel, 2011). Current theories on time-based expectancy assume that the correlation between interval duration and event is learned by an associative learning mechanism (Los, Kruijne, & Meeter, 2014; Thomaschke & Dreisbach, 2015; Thomaschke et al., 2011). Participants form associations between interval representations and representations of the predictable event aspect. For instance, a correlation between interval and required response would lead participants to associate one response with the short, and the other with the long interval (e.g., Thomaschke & Dreisbach, 2013). These associations are assumed to generate time-based expectancies. For our example with predictable responses, this would mean that, during the short interval, expectancy is directed at the response associated with that interval. When the short interval has passed without any target presentation, expectancy changes to the response associated with the long interval. This mechanism directly explains the time-based predictability effect, because confirmed expectancy usually leads to better performance than violated expectancy (see Los et al., 2014; Thomaschke & Dreisbach, 2015, for more detailed model formulations). All previous studies on time-based predictability assume explicit or implicit expectancy as the underlying cognitive mechanism (see Thomaschke & Dreisbach, 2015, for a review). Consequently, the time-based predictability effect is mostly referred to as time-based *expectancy* effect. The present study follows this convention from here on.

Time Expectancy

Time-based expectancy means expecting an event *based* on time. In contrast, the interval itself prior to an event can also be expected. This type of temporal expectancy is referred to as time expectancy (Thomaschke et al., 2015) and is defined as a prediction of the duration of an interval prior to an event. Time expectancy is conceptually independent from time-based expectancy, and is not the focus of the present study. However, time expectancy will be briefly discussed here, because it also occurs (as a side effect) in the time-event correlation paradigm, which is employed in the reported experiments. Time expectancy means that the duration of a warning interval before a target can be anticipated and has mostly been investigated by using the foreperiod paradigm, in which the duration between warning signal and target stimulus is manipulated (Los & Agter, 2005; Steinborn & Langner, 2012; Steinborn, Rolke, Bratzke, & Ulrich, 2008). A typical finding in the context of time expectancy is that response time decreases monotonously with increasing foreperiod, when the foreperiod duration varies randomly from trial to trial (Los, Kruijne, & Meeter, 2017; Steinborn & Langner, 2011; Steinborn, Rolke, Bratzke, & Ulrich, 2010).

One important aspect of time predictability with variable intervals is its inherent dynamic. Whenever a possible interval has passed by without target presentation on any trial, the longer (and hence still possible) intervals become more predictable. Consider a scenario with two possible equiprobable intervals. At the beginning of each trial, the interval is unpredictable, but once the short interval has passed by, the long one becomes 100% predictable. Thus, with variable intervals, interval predictability continually rises with interval duration. Note that the inherent temporal asymmetry in time expectancy does not apply to time-based expectancy. In time-based expectancy, the shorter of two intervals can have the same predictability as the longer one (and always had in previous studies; see Thomaschke & Dreisbach, 2015, for a review).

Although the above-described time-event correlation paradigm (Wagener & Hoffmann, 2010) is actually designed to manipulate time-based event predictability, it also necessarily involves time expectancy, because intervals vary randomly between trials in this paradigm. Thus, time predictability is always higher at the longer than at the shorter interval. Accordingly, previous studies with the time-event correlation paradigm typically found better performance at the longer than at the shorter interval (Thomaschke et al., 2011; Wagener & Hoffmann, 2010). However, the effects of time expectancy typically did not interact with the effects of time-based event expectancy (see Thomaschke & Dreisbach, 2015, for a review). This means, time-based expectancy is usually present at the short as well as at the long interval. Consequently, in the present study, it is not predicted that effects of time-based expectancy interact with effects of time expectancy.

Time-Based Expectancy in Task Switching

As mentioned above, although task predictability is a major topic in current research on task switching, the effects of time-based task expectancy have not yet been investigated and research on time-based expectancy has exclusively been confined to single task studies so far. This lack of research interest is particularly surprising as it is known that in most areas of applied multitasking, like communication, sports, or human machine interaction, delays are predictive with regard to the following task (Roberts & Francis, 2013; Shahar, Meyer, Hildebrandt, & Rafaely, 2012; Thomaschke & Haering, 2014).

As time-based task expectancy is likely to have a strong impact on cognitive processing and behavior in task switching, the aim of Experiments 1–3 was to test, whether time-based task predictability affects behavior in a task-switching scenario. The duration of the interval predicted one of two possible tasks with a certain probability (90% in Experiment 1, 80% in Experiment 2 and 70% in Experiment 3). We expected a specific time-based expectancy effect for RTs after frequent combinations of interval and task, compared to infrequent and, therefore unpredictable, combinations of interval and task.

Moreover, some studies investigating cognitive control in task switching were able to show that anticipatory cognitive control seems to enhance preparation not only for task sets but also for task transitions (i.e., task switches and task repetitions). Farooqui and Manly (2015) showed that performance significantly improved on switch trials after cues that predicted task switches, and that their participants were entirely unaware of the subliminal cues predicting task switches. They concluded that unconscious cognition seems to be able to implicitly use subliminal information in a goal-directed manner for anticipatory control (for similar results see Reuss, Desender, Kiesel, & Kunde, 2014). Dreisbach and Haider (2006) also reported a dynamical adjustment of cognitive control to expected task requirements while switching between cognitive tasks. This was evidenced by strong preparation effects in high-switch blocks (75% task switches), especially when specific probability cues were provided before each trial. Therefore, the aim of Experiments 4 and 5 was to test, whether time-based predictability also affects behavior in a task-switching scenario when not the task itself is directly predictable by time, but the transition of the task (switch vs. repetition), and if participants would thereby adjust their anticipatory cognitive control to expected switch requirements. As the duration of the interval predicted the upcoming switch or repetition of a task in the current trial (with 90% probability in Experiment 4 and 80% probability in Experiment 5), we predicted a specific temporal expectancy effect for RTs after frequent combinations of interval and transition, compared to infrequent, and therefore unpredictable, combinations of interval and transition.

Experiment 1

The purposes of Experiment 1 were to test, whether time-based task predictability affects behavior in a task-switching scenario and to serve as a baseline for further experiments concerning time-based task expectancy. To examine this question, a combination of the standard task-switching paradigm and the time-event correlation paradigm (Wagener & Hoffmann, 2010) was used. The procedure involved two different intervals (500 ms and 1,500 ms) and two different tasks (magnitude judgment task and parity judgment task). The intervals predicted the upcoming task type (i.e., parity judgment task vs. magnitude judgment task) in the current trial with 90% probability. It was predicted that participants learn the associations between interval and task type, thereby building up time-based expectancies for task type. These time-based expectancies should be observable by faster responses in trials with frequent combinations of interval and task type, compared to trials with infrequent combinations of interval and task type.

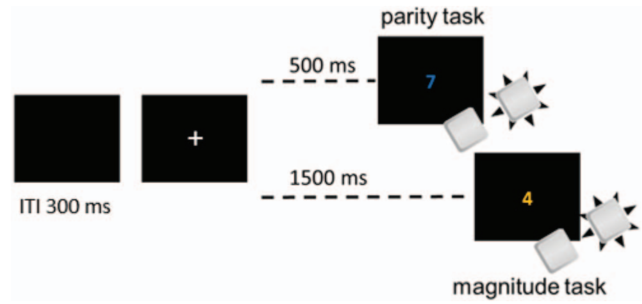

Figure 1. Exemplary trial procedure: The fixation cross marked the predictive interval and was presented either for 500 ms (short interval), or for 1,500 ms (long interval). The interval duration predicted the upcoming task with 90% probability in Experiment 1. The color of the target stimulus indicated which task participants had to perform in the current trial, and thus served as an explicit task cue. Responses were given with the same two buttons for both tasks. Trials were separated by a constant intertrial interval (ITI) of 300 ms. See the online article for the color version of this figure.

Method

Participants. Thirty-two participants (20 females) took part in the experiment. The ages ranged from 17 to 61 years, $M = 26.72$, $SD = 10.45$. Participants were either students from the universities of Regensburg and Freiburg, who received course credits, or inhabitants of the city of Freiburg or Regensburg, who received monetary compensation for their participation. All participants had normal or corrected-to-normal vision and gave their informed consent before participation. Participants were treated according to the ethical standards of the American Psychological Association. Sample size was determined according to the effect size reported in previous studies on time-based expectancy ($d = 0.5$). Power analyses ($1 - \beta = 0.8$) yielded a minimum number of 27 participants. For reasons of counterbalancing we rounded to 32 participants.

Apparatus and stimuli. Participants responded by key presses either on a *QUERTZ* keyboard with the right and the left index-finger, or on two response buttons on a serial response box (Psychology Software tools), which was centrally aligned in front of the computer screen. Target Stimuli were yellow or blue numbers between 1 and 9, except 5, presented against a black background at a viewing distance of 50 cm. The size of the stimuli was approximately 8×5 mm. The fixation cross was the "+" symbol (white font color, Arial typeface, approximately 6×6 mm). All stimuli were presented centrally on the screen.

Procedure. An exemplary trial procedure is displayed in Figure 1. Each trial started with a blank screen for 300 ms (intertrial interval, ITI), which was followed by the presentation of a fixation cross for a variable interval of either 500 ms or 1,500 ms. After this interval, the target stimulus was presented. The order of stimuli was randomized, and each stimulus occurred with equal probability. Depending on the color of the target stimulus, participants had to judge whether the displayed number was smaller or larger than 5 (magnitude judgment task) or whether it was odd or even (parity judgment task). The mapping of colors to tasks was counterbalanced across participants. Responses were given with the same two buttons for both tasks. The mapping of responses to keys was also counterbalanced across participants. Participants were instructed to respond as fast and as correct as possible. After the detection of an error, the word *Fehler!* (German for "Error!") was displayed in red on a black screen for 1,500 ms. After correct responses, no explicit feedback was given. The duration of the interval predicted the upcoming task type in the current trial with 90% probability, which means that one task occurred frequently after the short interval, while the other task appeared frequently after the long interval. Both intervals and tasks appeared with same overall frequencies and the mapping of tasks to intervals was counterbalanced across participants. Participants were not informed that the intervals had different lengths, or that these interval lengths were correlated with tasks.

The experiments consisted of two sessions of 30 min each, which were tested on consecutive days. Both sessions of the experiment consisted of four blocks each: one learning block, and three test blocks. Each block comprised 120 trials. The only difference between learning blocks and test blocks was that after the detection of an error, the instruction was once again presented in silver font color on a black screen for 8,000 ms in the learning blocks, before the next trial started with the presentation of the ITI. Between blocks, participants could take a break, which they could terminate themselves by pressing the spacebar. After the second session of the experiment, participants were asked by the experimenter whether they had noticed any temporal regularities in the experiment.

Results

Following earlier studies on time-based expectancy, we analyzed only the second session (e.g., Thomaschke & Dreisbach, 2013). Data from the learning blocks, from the first three trials of each test block, as well as trials with number repetitions and trials following an error trial were excluded from analyses. In addition, we excluded trials with reaction times (RTs) <100 ms from analyses. For each factor combination, each block and each participant, we removed RTs with a deviation of more than 3 *SD* from the respective mean RT before RT analyses (Bush, Hess, & Wolford, 1993). Furthermore, trials with errors were removed from the RT analyses. Three-factor repeated measures ANOVAs with the factors interval (500 vs. 1,500 ms), transition (switch vs. repetition), and predictability of interval–task combination (predictable vs. unpredictable) were conducted separately for RTs and error rates.

With regard to RTs, the three main effects were significant (see Figure 2). Responses were faster after short than after long intervals, $F(1, 31) = 7.42$, $p = .010$, $\eta_p^2 = .193$, and responses to task repetitions were faster than to task switches, $F(1, 31) = 9.88$, $p = .004$, $\eta_p^2 = .242$. In trials with predictable combinations of interval and task, responses were significantly faster than in trials with unpredictable combinations of interval and task, $F(1, 31) = 9.72$, $p = .004$, $\eta_p^2 = .239$. The only significant interaction for RTs was between interval, transition and predictability, $F(1, 31) = 4.97$, $p = .033$, $\eta_p^2 = .138$.

On the basis of the reported three-factor-interaction, we conducted a two-factor repeated measures ANOVA with the factors interval (500 vs. 1,500 ms) and predictability of interval–task combination (predictable vs. unpredictable) separately for task repetition and for task switch. For the condition task repetition, the two main effects were significant. RTs were faster after short intervals than after long intervals, $F(1, 31) = 5.45$, $p = .026$, $\eta_p^2 = .150$ and RTs were significantly faster in trials with predictable interval–task combination than in trials with unpredictable interval–task combination, $F(1, 31) = 6.13$, $p = .019$, $\eta_p^2 = .165$. There was no interaction between the two factors, $F < 1$.

For task switches, the main effect of predictability, $F(1, 31) = 7.47$, $p = .010$, $\eta_p^2 = .194$, and the interaction between interval and predictability, $F(1, 31) = 5.72$, $p = .023$, $\eta_p^2 = .156$ were significant. Post hoc *t* tests revealed that in trials with a task switch, the predictability effect was significant when the task was preceded by a long interval of 1,500 ms, $t(31) = -2.80$, $p = .009$, $d = -2.90$.[1] We next calculated Bayes factor for paired *t* test designs via a web-based program that computes the scaled JZS Bayes factor for input values of *t* and the sample size *N* (pcl.missouri.edu; Rouder, Speckman, Sun, Morey, & Iverson, 2009). The Bayesian approach is a model selection procedure that indicates the likelihood ratio of two or more hypotheses on the basis of the given data. Thus, Bayesian analysis provides the possibility of evaluating evidence in favor of the (null-) hypothesis. In this context, the Bayes factor (BF) indicates how strong the data is in favor of the (null-) hypothesis, with the convention that a BF between 1 and 3 indicates anecdotal evidence, a BF between 3 and 10 moderate evidence, and a BF above 10 strong evidence for a (null-) hypothesis (Lee & Wagenmakers, 2013). For $N = 32$ and $t = -2.8$, the corresponding JZS Bayes factor in favor of the alternative hypothesis equaled 4.95. This means that the alternative hypothesis (there is a predictability effect in trials with a task switch after an interval of 1,500 ms) was >4 times as likely as the H0 (no difference between predictable and unpredictable interval-task combinations in trials with a task switch after an interval of 1,500 ms). In trials with short intervals of 500 ms, the result pattern was descriptively in the opposite direction, $t(31) = 1.47$, $p = .150$, $d = 1.38$. Analysis revealed that the JZS Bayes factor in favor of the null hypothesis equaled 1.99. This means that the null hypothesis (no difference between predictable and unpredictable interval-task combinations in trials with a task switch after an interval of 500 ms) was <2 times as likely as the alternative hypothesis (there exists a difference between predictable and unpredictable interval-task combinations in trials with a task switch after an interval of 500 ms). Thus, we can conclude that our Bayes analysis revealed only anecdotal evidence in favor of the null hypothesis in this context. The main effect of interval did not gain significance, $F(1, 31) = 2.55$, $p = .121$, $\eta_p^2 = .076$.

With regard to error rates, only the main effect of predictability was significant. Error rates were significantly lower in trials with predictable interval–task combination than in trials with unpredictable interval–task combination, $F(1, 31) = 5.08$, $p = .031$, $\eta_p^2 = .141$. No other main effect or interaction gained significance.

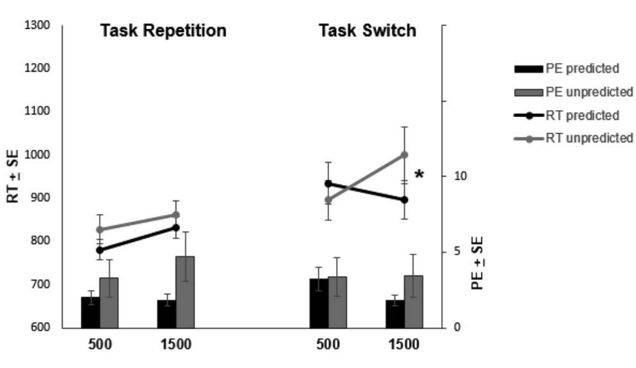

Figure 2. Main results of Experiment 1: Mean reaction times (RTs; in ms; lines) and percentages of errors (PEs in %; bars), depending on predictability of interval-task combination, are displayed separately for task transition (task repetition vs. task switch), and interval duration (500 ms vs. 1,500 ms). Error bars represent 1 standard error of the mean. Asterisks denote significance in a *t* test with a significance level of .05.

Discussion

In Experiment 1, we investigated whether time-based task predictability affects behavior in a task-switching scenario. The results revealed that participants responded significantly faster in trials with predictable combinations of interval and task compared to trials with unpredictable combinations of interval and task. The significant time-based task expectancy effect thus showed that participants were able to form time-based task expectancies and to expect one task after the short interval and the other task after the long interval. None of the participants noticed any temporal regularities during the whole experiment. Moreover, participants responded faster in trials with the short interval compared to trials with the long interval which seems quite surprising as time expectancy should be always higher at the longer than at the shorter interval. Thus, according to previous studies employing the time-event correlation paradigm (Thomaschke et al., 2011), we expected better performance at the longer than at the shorter interval. Possible explanations for this unexpected finding draw on phasic alertness or time uncertainty and shall be further elaborated in the General Discussion. The fact that participants responded significantly faster in trials with a task repetition compared to trials with a task switch reflects the typical switch costs in task switching (see also Kiesel et al., 2010).

Furthermore, we found a significant three-way interaction between the factors interval, task transition and predictability of interval-task combination. In trials with task switches, there was an expectancy effect when the task was preceded by the long interval

[1] The effect size *d* estimates Cohen's *d* for difference scores in a within-subjects test, and was bias-corrected according to Gibbons, Hedeker, and Davis (1993, Equations 3,17,19).

of 1,500 ms. In trials with task switches and the short interval of 500 ms, the result pattern was, at least descriptively, in the opposite direction. As we did not find this three-way interaction in Experiments 2 and 3, we will not discuss this finding in detail here.

Thus, the results of Experiment 1 speak in favor of the fact that participants are able to form time-based task expectancies in the task-switching paradigm. To find out whether time-based expectancy can be also formed with a lower degree of predictability, which is typically employed in studies on time-based expectancy, we conducted Experiment 2.

Experiment 2

In previous studies on time-based event expectancy, events were temporally predictable with 80% probability (see Wagener & Hoffmann, 2010). As task preparation might be cognitively more complex than response preparation, we have chosen a higher predictability for the initial test of time-based task expectancy in Experiment 1. Here we test whether time-based task expectancy can also be formed under predictability conditions typically employed in time-based expectancy research.

Method

Participants. Thirty-two participants (22 females) took part in the experiment. The ages ranged from 18 to 39 years, $M = 23.97$, $SD = 4.93$. Again, participants were students from the universities of Regensburg or Freiburg or inhabitants of the cities of Regensburg or Freiburg, who received course credits or monetary compensation for their participation. All participants fulfilled the same criteria as in Experiment 1.

Procedure. The procedure was the same as in Experiment 1, except for the fact that the duration of the interval predicted the upcoming task with 80% probability in Experiment 2, instead of 90% probability in Experiment 1.

Results

Data preprocessing was the same as in Experiment 1 and also RT and PE analysis were conducted as in Experiment 1. RTs and error rates are shown in Figure 3. With regard to RTs, the three main effects were significant. Responses were faster after short than after long intervals, $F(1, 31) = 5.32$, $p = .028$, $\eta_p^2 = .146$, and responses to task repetitions were faster than to task switches, $F(1, 31) = 34.12$, $p < .001$, $\eta_p^2 = .524$. In trials with predictable combinations of interval and task, responses were significantly faster than in trials with unpredictable combinations of interval and task, $F(1, 31) = 9.28$, $p = .005$, $\eta_p^2 = .230$. The only significant interaction for RTs was between interval and transition, $F(1, 31) = 6.47$, $p = .016$, $\eta_p^2 = .173$, meaning that RTs were faster after an interval of 500 ms than after an interval of 1,500 ms in trials with a task repetition, whereas no such effect of interval was observed in trials with a task switch.

With regard to error rates, no main effect or interaction was significant.

Discussion

Experiment 2 investigated whether the effect of time-based task expectancy is also observable with only 80% trials with frequent combinations of interval and task instead of 90% trials with frequent combinations of interval and task (see Experiment 1). The results of Experiment 2 confirmed the results of Experiment 1 and speak, again, in favor of the fact that participants are able to form time-based task expectancies in the task-switching paradigm. The results revealed a significant time-based expectancy effect, which means that participants responded significantly faster in trials with predictable combinations of interval and task compared to trials with unpredictable combinations of interval and task. Like in Experiment 1, participants did not notice any temporal regularities, responded significantly faster in trials with a short interval compared to trials with a long interval and showed the typical task-switching costs. Although the degree of predictability was reduced compared to the degree of predictability in Experiment 1, the time-based expectancy effect was still observable in Experiment 2. To investigate whether the time-based task expectancy effect would be also observable with an even smaller degree of predictability, we conducted Experiment 3.

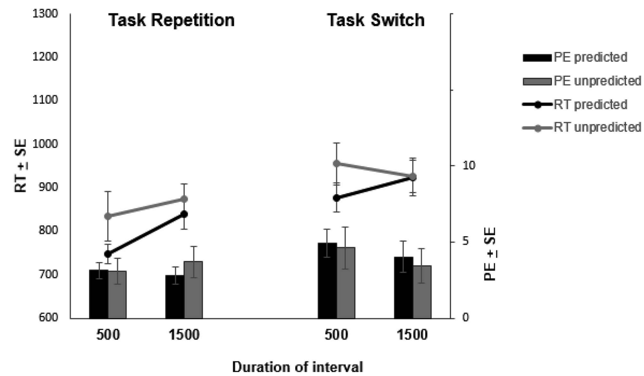

Figure 3. Main results of Experiment 2: Mean reaction times (RTs in ms; lines) and percentages of errors (PEs in %; bars), depending on predictability of interval-task combination, are displayed separately for task transition (task repetition vs. task switch), and interval duration (500 ms vs. 1,500 ms). Error bars represent 1 standard error of the mean.

Experiment 3

Experiment 2 showed that the effect of time-based task expectancy was also observable with a smaller degree of predictability (80% in Experiment 2 instead of 90% in Experiment 1). The purpose of the third experiment was to test whether an even smaller degree of predictability would impair the strength of time-based task expectancy or whether the effect of time-based task expectancy would be still observable given different degrees of predictability.

Method

Participants. Thirty-two participants (26 females) took part in the experiment. The ages ranged from 18 to 29 years, $M = 22.19$, $SD = 2.92$. Participants were students from the universities of Regensburg or Freiburg or inhabitants of the cities of Regensburg or Freiburg, who received course credits or monetary compensation for their participation. All participants fulfilled the same criteria as in the previous experiments.

Procedure. The procedure was the same as in Experiments 1 and 2. Compared to Experiments 1 and 2, the degree of predictability was even more reduced in Experiment 3 and interval length predicted the upcoming task in the current trial with only 70% probability.

Results

Data preprocessing was the same as in Experiments 1 and 2 and also RT and PE analysis were conducted as in Experiments 1 and 2. With regard to RTs, only the three main effects were significant (see Figure 4). Responses were faster after short than after long intervals, $F(1, 31) = 11.86$, $p = .002$, $\eta_p^2 = .277$, and responses to task repetitions were faster than to task switches, $F(1, 31) = 28.21$, $p < .001$, $\eta_p^2 = .476$. In trials with predictable combinations of interval and task, responses were significantly faster than in trials with unpredictable combinations of interval and task, $F(1, 31) = 12.31$, $p = .001$, $\eta_p^2 = .284$.

With regard to error rates, no main effect or interaction attained significance.

To investigate whether the between-subjects factor experiment interacted with interval, task transition or predictability of interval-task combination, we conducted a cross-experiment analysis. Results showed that the three main effects were significant and that experiment did not interact with any of these main effects. Responses were faster after the short than after the long interval, $F(1, 93) = 24.25$, $p < .001$, $\eta_p^2 = .207$ and this effect did not differ between experiments, $F(2, 93) = .96$, $p = .386$, $\eta_p^2 = .020$. Reaction times for task repetitions were faster than for task switches, $F(1, 93) = 56.93$, $p < .001$, $\eta_p^2 = .380$ and again, this effect did not differ between experiments, $F(2, 93) = 1.76$, $p = .179$, $\eta_p^2 = .036$. Responses were faster in trials with predictable combinations of interval and task compared to trials with unpredictable combinations of interval and task, $F(1, 93) = 29.60$, $p < .001$, $\eta_p^2 = .241$. This effect did not differ between experiments, $F(2, 93) = .35$, $p = .707$, $\eta_p^2 = .007$. Given this null-effect, we next performed a Bayesian rANOVA with default prior scales using JASP (JASP team, Version 0.8.1.1). Our Bayesian analyses showed that the null-hypothesis model for the interaction between predictability of interval–task combination and experiment (no difference of time-based task expectancy between the three experiments) was >32 times as likely as the H1 (BF = 32.420).

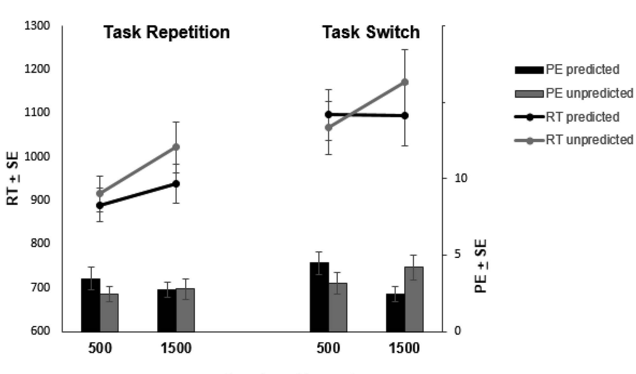

Figure 4. Main results of Experiment 3: Mean reaction times (RTs in ms; lines) and percentages of errors (PEs in %; bars), depending on predictability of interval–task combination, are displayed separately for task transition (task repetition vs. task switch) and interval duration (500 ms vs. 1,500 ms). Error bars represent 1 standard error of the mean.

Apart from a significant interaction between interval and task transition, $F(1, 93) = 4.27$, $p = .042$, $\eta_p^2 = .044$, which did not interact with experiment, $F(2, 93) = .86$, $p = .426$, $\eta_p^2 = .018$ there were no other significant interactions. The interaction between task transition and predictability of interval–task combination did not gain significance, $F(1, 93) = 3.64$, $p = .059$, $\eta_p^2 = .038$. Bayesian rANOVA revealed that the null-hypothesis (no difference of time-based task expectancy between task repetitions and task switches) was >6 times as likely as the H1 (BF = 6.129). Surprisingly, we found a main effect for experiment, $F(2, 93) = 4.54$, $p = .013$, $\eta_p^2 = .089$, meaning that participants responded slower in Experiment 3 compared to Experiments 1 and 2.

With regard to error rates, no main effect or interaction gained significance in the cross-experiment analysis.

Discussion

Experiment 3 investigated whether the time-based task expectancy effect was also observable with an even smaller degree of predictability, namely only 70% trials with frequent combinations of interval and task instead of 90% (Experiment 1) or 80% (Experiment 2) trials with frequent combinations of interval and task. Results revealed a time-based task expectancy effect, meaning that participants responded significantly faster in trials with predictable combinations of interval and task compared to trials with unpredictable combinations of interval and task. Like in Experiments 1 and 2, participants did not notice any temporal regularities during the whole experiment, responded again significantly faster after the short interval than after the long interval and showed the typical switch costs. The results of the cross-experiment analysis showed that the time-based task expectancy effect was not at all affected by different degrees of predictability, ranging from 90% in Experiment 1 over 80% in Experiment 2 to 70% in Experiment 3, and thus seems to be rather stable across different degrees of predictability. Bayesian analysis further supported this finding. Furthermore, the interaction between task transition and predictability of interval–task combination did not gain significance in the cross-experiment analysis and thus it can be concluded that time-based task expectancy seems to be not switch-specific. This finding was further supported by a Bayesian analysis.

It is interesting to note that Experiments 1 through 3 revealed that participants seem to be able to associate one time interval with one specific task and the other time interval with the other task. This means that there must be some kind of updating of time-based task expectancy during the course of the time interval. Participants expect one task after the short interval and as soon as the short interval of 500 ms has passed without any stimulus presentation, the strength of expectancy for this task gets smaller and the other task is expected instead. This implies a rather flexible task-specific preparation during the temporal course of the pretarget interval, which, to our knowledge, could be shown for the first time.

As studies have shown that anticipatory cognitive control can enhance the preparation not only for upcoming task types but also for upcoming task transitions (see Farooqui & Manly, 2015), Experiment 4 was conducted to investigate whether not only the task itself but also the task transition (task switch vs. task repetition) can be predicted based on time in the task-switching paradigm.

Experiment 4

Experiments 1 through 3 demonstrated that participants formed time-based task expectancies, and that they used this expectancy for task preparation, which was shown by better performance in trials with frequent combinations of interval and task compared to trials with infrequent combinations of interval and task. The purpose of Experiment 4 was to test whether time-based predictability also affects behavior in a task-switching scenario when not the task is directly predictable by time, but the transition of the task (switch vs. repetition). Note that, given that participants only switched between two tasks, the specific task could still be inferred from the interval and the knowledge about the previous task. We expected faster responses in trials with predictable combinations of interval and task transition compared to trials with unpredictable combinations of interval and task transition. Because of the fact that previous studies revealed more demanding control processes (see Forstmann, Brass, Koch, & von Cramon, 2005) for transition cueing in comparison to task cueing, we used a high degree of predictability (90%) in Experiment 4 for the initial test whether participants are able to expect a task transition based on a preceding predictive time interval.

Method

Participants. Thirty-two participants (23 females) took part in the experiment. The ages ranged from 19 to 60 years, $M = 25.38$, $SD = 6.99$. Participants were students from the universities of Regensburg or Freiburg or inhabitants of the cities of Regensburg or Freiburg, who received course credits or monetary compensation for their participation and who fulfilled the same criteria as in the previous experiments.

Procedure. The procedure was the same as described in Experiments 1 through 3, with the exception that the duration of the interval predicted not the upcoming task in the current trial, but the upcoming task transition (switch vs. repetition) with 90% probability.

Results

Data preprocessing was the same as in Experiments 1 through 3. Please note that a three-factor repeated measures ANOVA with the factors interval, transition and predictability of interval–transition combination was not possible, because the factors interval and transition were no longer independent from each other in this experiment. As the duration of the interval predicted the upcoming task transition with 90% probability, an interval–transition combination could be either predictable or unpredictable for one participant (dependent from the respective test condition). Therefore, we conducted two repeated measures ANOVAs this time. First, we conducted two-factor repeated measures ANOVAs with the factors transition (switch vs. repetition) and predictability of interval–transition combination (predictable vs. unpredictable) separately for RTs and error rates (see Figure 5A). With regard to RTs, the two main effects were significant. RTs were faster in trials with task repetitions compared to trials with task switches, $F(1, 31) = 13.06$, $p = .001$, $\eta_p^2 = .296$ and RTs were faster in trials with predictable interval–transition combinations compared to trials with unpredictable interval-transition combinations, $F(1, 31) = 14.89$, $p = .001$, $\eta_p^2 = .324$. The interaction of the two factors was not significant, $F < 1$.

With regard to error rates, only the main effect of transition was significant, which means that participants made less errors in trials with task repetitions compared to trials with task switches, $F(1, 31) = 5.41$, $p = .027$, $\eta_p^2 = .149$. Neither the main effect for predictability of interval–transition combination, $F < 1$, nor the interaction between the two factors, $F(1, 31) = 2.78$, $p = .106$, $\eta_p^2 = .082$ gained significance.

We also conducted two-factor repeated measures ANOVAs with the factors interval (500 vs. 1,500 ms) and predictability of interval–transition combination (predictable vs. unpredictable) separately for RTs and error rates (see Figure 5B). With regard to RTs, the two main effects were significant. RTs were faster in trials with a short interval of 500 ms compared to trials with a long interval of 1,500 ms, $F(1, 31) = 8.14$, $p = .008$, $\eta_p^2 = .208$ and RTs were also faster in trials with predictable interval–transition combination compared to trials with unpredictable interval-transition combination, $F(1, 31) = 14.89$, $p = .001$, $\eta_p^2 = .324$. The interaction between the two factors was not significant, $F < 1$.

With regard to error rates, neither the two main effects of interval and predictability of interval–transition combination, nor the interaction between the two factors were significant, all $F < 1$.

Discussion

Experiment 4 investigated whether participants are able to form time-based expectancies when time predicts transition with 90% probability in the task-switching paradigm. Like in Experiments 1 through 3, participants responded again faster in trials with the short interval compared to trials with the long interval and showed the typical switch costs. More importantly, the results revealed significantly faster responses in trials with frequent combinations of interval and task transition compared to trials with infrequent combinations of interval and task transition. It is important to note that participants again did not notice any temporal regularities. It seems as if participants were able to form time-based expectancies and to use them in an anticipatory manner for task transition preparation. Because we assumed higher cognitive control demands for time-based expectancy of task transition in comparison to time-based expectancy of task type, we started with a high degree of predictability in Experiment 4. In Experiment 5, we wanted to investigate whether the time-based task transition effect would also be observable with a smaller degree of predictability.

Experiment 5

The purpose of Experiment 5 was to test whether a smaller degree of predictability of interval–transition combination allows determining whether time-based transition expectancy could be formed with different strengths of predictability, or whether a smaller degree of predictability would impair the strength of time-based transition expectancy.

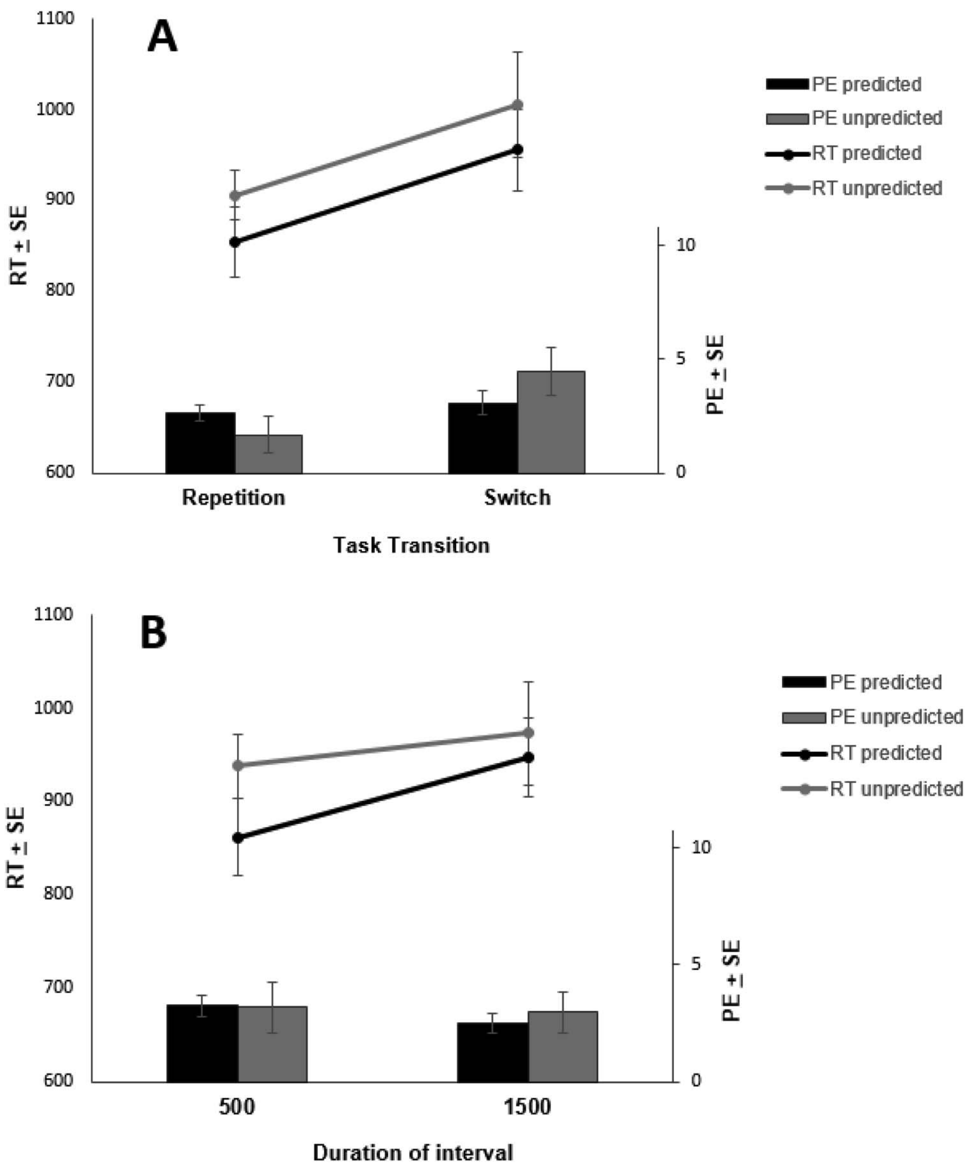

Figure 5. Main results of Experiment 4: In Panel A, mean reaction times (RTs in ms; lines) and percentages of errors (PEs in %; bars), depending on predictability of interval–transition combination, are displayed separately for task repetitions and for task switches. In Panel B, mean reaction times (RTs in ms; lines) and percentages of errors (PEs in %; bars), depending on predictability of interval–transition combination, are displayed separately for interval duration (500 ms vs. 1,500 ms). Error bars represent 1 standard error of the mean.

Method

Participants. Thirty-two participants (21 females) took part in the experiment. The ages ranged from 18 to 59 years, $M = 22.13$, $SD = 7.39$. Participants were students from the university of Freiburg or inhabitants of the city of Freiburg, who received course credits or monetary compensation for their participation. All participants fulfilled the same criteria as in the previous experiments.

Procedure. The procedure was the same as described in Experiment 4, but instead of 90% trials with frequent combinations of interval and transition (see Experiment 4), the degree of predictability was reduced in Experiment 5 and the duration of the interval predicted the upcoming task transition (switch or repetition) only with 80% probability.

Results

Data preprocessing was the same as in Experiments 1 through 4 and RT and PE analysis were the same as in Experiment 4. We first conducted two-factor repeated measures ANOVAs with the factors transition (switch vs. repetition) and predictability of interval–transition combination (predictable vs. unpredictable) separately for RTs and error rates (see Figure 6A). With regard to RTs, only the main effect of transition was significant. RTs were faster in trials with task repetitions compared to trials with task switches, $F(1, 31) = 8.56$, $p = .006$, $\eta_p^2 = .216$. Neither the main effect of predictability of interval–transition combination, $F(1, 31) = 1.68$, $p = .204$, $\eta_p^2 = .051$, nor the interaction between the two factors, $F < 1$, were significant.

With regard to error rates, only the interaction of the factors transition and predictability was significant, $F(1, 31) = 5.70$, $p = .023$, $\eta_p^2 = .155$. Participants committed fewer errors in trials with predictable interval–transition combination only for task repetitions, and not for switches. However, both comparisons were not significant (for repetitions: $t(31) = -1.48$, $p = .148$, $d = -1.69$, scaled JZS Bayes Factor in favor of the null hypothesis: 1.97; for switches: $t(31) = 1{,}40$, $p = .173$, $d = 1.23$, scaled JZS Bayes Factor in favor of the null hypothesis: 2.18). Neither the main effect for transition, $F < 1$, nor the main effect for predictability of interval–transition combination, $F < 1$, gained significance.

We also conducted two-factor repeated measures ANOVAs with the factors interval (500 vs. 1,500 ms) and predictability of interval–transition combination (predictable vs. unpredictable) separately for RTs and error rates (see Figure 6 B). With regard to RTs, neither the two main effects of interval, $F(1, 31) = 1.98$, $p = .170$, $\eta_p^2 = .060$ and predictability of interval–transition combina-

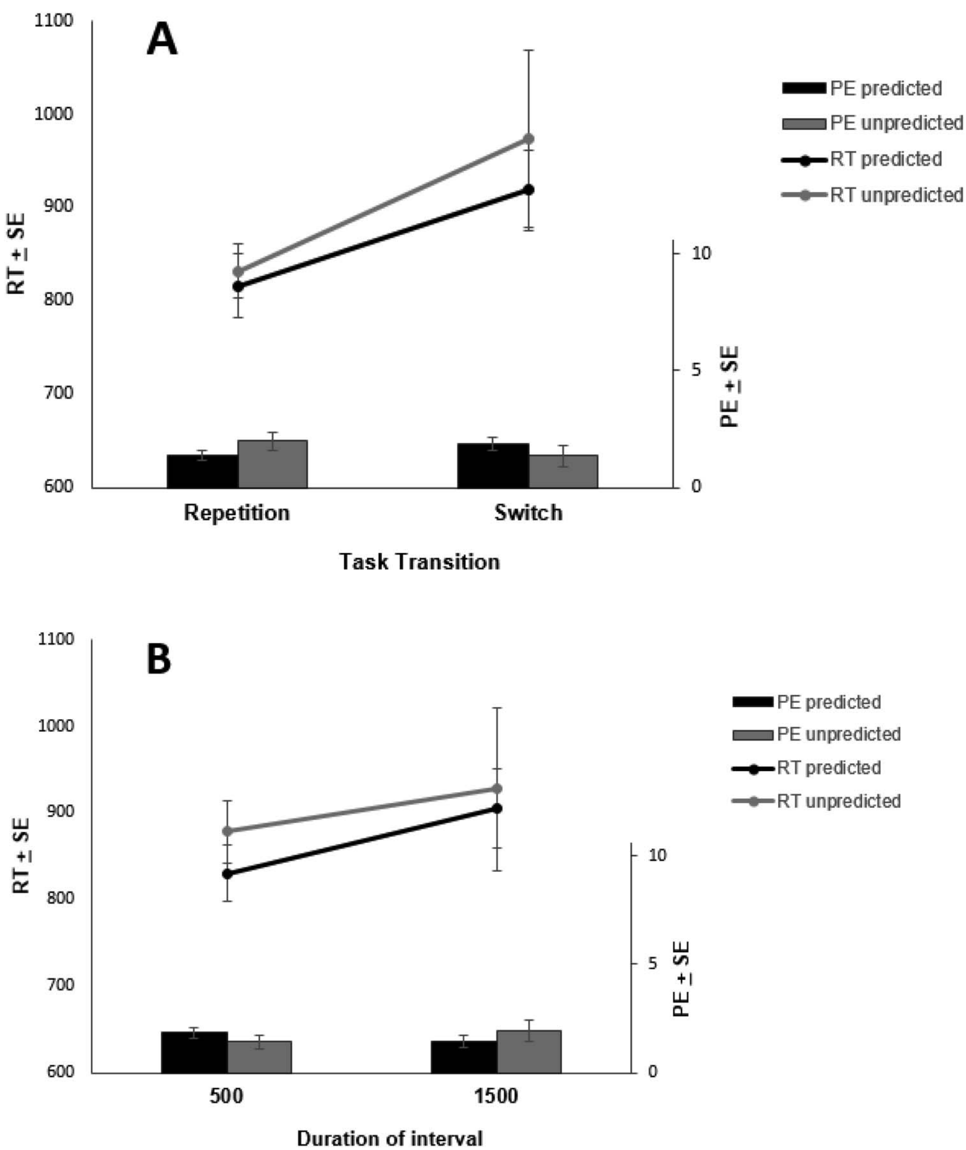

Figure 6. Main results of Experiment 5: In Panel A, mean reaction times (RTs; in ms; lines) and percentages of errors (PEs in %; bars), depending on predictability of interval–transition combination, are displayed separately for task repetitions and task switches. In Panel B, mean reaction times (RTs in ms; lines) and percentages of errors (PEs in %; bars), depending on predictability of interval–transition combination, are displayed separately for interval duration (500 ms vs. 1,500 ms). Error bars represent 1 standard error of the mean.

tion, $F(1, 31) = 1.68$, $p = .204$, $\eta_p^2 = .051$ nor the interaction of the two factors, $F < 1$, were significant.

Also with regard to error rates, neither the main effects of interval, $F < 1$, and predictability of interval–transition combination, $F < 1$, nor the interaction between the two factors, $F(1, 31) = 1.85$, $p = .184$, $\eta_p^2 = .056$ were significant.

To investigate whether the effects of task transition and predictability of the interval-transition combination differed between Experiments 4 and 5, we conducted three-factor repeated measures ANOVAs with the within-subject factors task transition and predictability of interval-transition combination and the between-factor experiment separately for RTs and error rates. Responses were faster after task repetitions than after task switches, $F(1, 62) = 19.70$, $p < .001$, $\eta_p^2 = .241$ and this effect did not differ between experiments, $F < 1$. Responses were also faster in trials with predictable combinations of interval and task compared to trials with unpredictable combinations of interval and task transition, $F(1, 62) = 8.05$, $p = .006$, $\eta_p^2 = .115$. It is surprising that predictability of interval–transition combination did not interact with experiment, $F < 1$. Given this null-effect, we next performed a Bayesian rANOVA. Our Bayesian analyses showed that the null-hypothesis model for the interaction between transition expectancy and experiment (no difference of time-based transition expectancy between the two experiments) was >5 times as likely as the H1 (BF = 5.283). There was no interaction between task transition and predictability of interval–transition combination, $F < 1$. Bayesian rANOVA showed that the null-hypothesis model for the interaction between task transition and predictability of interval–transition combination (there is no difference for the transition expectancy effect between task repetitions and task switches) was >5 times as likely as the H1 (BF = 5.065).

With regard to error rates the main effect for task transition gained significance, $F(1, 62) = 4.06$, $p = .048$, $\eta_p^2 = .061$ and interacted with experiment, $F(1, 62) = 4.65$, $p = .035$, $\eta_p^2 = .070$, which means that participants made more errors in trials with a task switch compared to trials with a task repetition in Experiment 4, whereas the error rate was nearly the same for repetitions and switches in Experiment 5. Furthermore there was a significant three-way interaction between task transition, predictability of interval–transition combination and experiment, $F(1, 62) = 5.48$, $p = .022$, $\eta_p^2 = .081$, meaning that there was a significant interaction between task transition and predictability of interval–task combination in Experiment 5 resulting in higher error rates for infrequent combinations of interval and task transition than for frequent combinations of interval and task transition in trials with task repetitions and a reverse result pattern in trials with a task switch.

To investigate whether the effects of interval and predictability of interval-transition combination differed between Experiments 4 and 5, we conducted three-factor repeated measures ANOVAs with the within-subject factors interval and predictability of interval-transition combination and the between-factor experiment separately for RTs and error rates. Results showed that the two main effects were significant and that experiment did not interact with any of these main effects. Responses were faster after the short interval than after the long interval, $F(1, 62) = 6.25$, $p = .015$, $\eta_p^2 = .092$ and this effect did not differ between experiments, $F < 1$. Furthermore, responses were faster in trials with predictable combinations of interval and task compared to trials with unpredictable combinations of interval and task, $F(1, 62) = 8.05$, $p = .006$, $\eta_p^2 = .115$ and again, this effect did not differ between experiments, $F < 1$. Bayesian rANOVA revealed that the null-hypothesis model for the interaction between transition expectancy and experiment (no difference of time-based transition expectancy between the two experiments) was >5 times as likely as the H1 (BF = 5.240).

With regard to error rates only the main effect for experiment gained significance, $F(1, 62) = 5.84$, $p = .019$, $\eta_p^2 = .086$, meaning that participants made more errors in Experiment 4 compared to Experiment 5.

Discussion

Experiment 5 investigated whether participants are able to form time-based expectancies if there are only 80% trials with frequent combinations of interval and task transition instead of 90% trials with frequent combinations of interval and task transition (see Experiment 4). The results showed that participants showed the typical switch costs, but that there was no main effect for time-based transition expectancy for RTs. Again, none of the participants noticed any temporal regularities during the whole experiment. A cross-experiment analysis between Experiment 4 and 5, however, revealed that that there was a main effect for time-based transition expectancy, which surprisingly did not interact with experiment. Bayesian rANOVA provided further evidence in the direction of the null hypothesis (there seems to be no difference of transition expectancy effect between Experiments 4 and 5; Lee & Wagenmakers, 2013). Thus, we cannot conclusively infer that the formation of time-based task transition expectancy is dependent on the degree of predictability of interval–transition combination.

General Discussion

In the present study, we investigated whether participants are able to form time-based expectancies for task types and for task transitions and to use these expectancies in an anticipatory manner for preparation in the task-switching paradigm. Using a combination of the standard task-switching paradigm and the time-event correlation paradigm (Wagener & Hoffmann, 2010) participants had to classify numbers either as odd or even or smaller or larger than five. The color of the target stimulus indicated, which of the two tasks the participants had to perform in the current trial. The target stimuli were preceded by either a short interval of 500 ms or a long interval of 1,500 ms. Crucially, the preceding time interval predicted the upcoming task type with 90% probability (Experiment 1), 80% probability (Experiment 2) or 70% probability (Experiment 3). In two other experiments, the time interval only indirectly predicted the upcoming task type (parity vs. magnitude judgment task), as it was directly predictive of the upcoming task transition (task switch vs. task repetition) with 90% probability (Experiment 4) or 80% probability (Experiment 5).

In the first three experiments, where the time interval preceding the target stimulus predicted the upcoming task type, responses were significantly faster in trials with frequent, and thus predictable, combinations of interval and task, compared to infrequent, and thus unpredictable, combinations of interval and task. A reliable time-based task expectancy effect was observed for three different degrees of predictability, ranging from 90% in Experiment 1 over 80% in Experiment 2 to 70% in Experiment 3. Cross-experiment analysis revealed that the time-based task expectancy effect did not differ between experiments and a Bayesian analysis further supported the null-hypothesis (no difference of the time-based task expectancy effect between Experiments 1 through 3). Thus, the time-based task expectancy effect seems to be rather stable across different degrees of predictability. The fact that the percentage of frequent interval-task combinations had apparently no influence on the size of the time-based expectancy effect seems quite surprising. Memory accounts based on multiple traces (Aufschnaiter, Kiesel, & Thomaschke, 2017; cf. Los et al., 2014; Thomaschke & Dreisbach, 2015) would predict that time-task contingencies should be consolidated in a multitude of memory traces, thereby strengthening the connection between successive neural activation states (i.e., temporal states) and expectancy-generating neural populations (for a detailed model description see Thomaschke & Dreisbach, 2015). Thus, these accounts would predict a modifying influence of the percentage of trials with consistent interval-task mapping on the size of the expectancy effect. As we did not find evidence for such a modifying influence of the percentage of frequent interval-task combinations on the size of the time-based expectancy effect, one could assume that an explicit learning process (i.e., participants being aware of the time-task contingencies) was involved. Such an explicit learning process would imply a rather rational strategy of expecting the most likely task at a given point in time, no matter how likely it might be. However, as none of the participants reported any explicit knowledge about temporal regularities after Experiments 1 through 3, a possible influence of the percentage of time-task contingencies on the size of the time-based task expectancy effect remains questionable and should be investigated in future studies.

Experiment 4 revealed that participants are also able to implicitly form time-based expectancies when time predicts an upcoming task transition instead of the task itself. This was evidenced by better performance in trials with predictable combinations of interval and task transition compared to trials with unpredictable combinations of interval and task transition. Taken together, the results of Experiment 4 indicate that the predictive value of the intervals' duration plays a crucial role for the cognitive processing of task transitions in task switching. Again, none of the participants reported any explicit knowledge about temporal regularities, which held also true for Experiment 5. The transition expectancy effect was, however, not observed with a lower degree of predictability (80%) in Experiment 5. As a cross-experiment analysis showed that transition expectancy did not differ between Experiments 4 and 5 and as this finding was further supported by a Bayesian analysis which revealed evidence in favor of the null-hypothesis (there is no difference of transition expectancy between Experiment 4 and 5), we cannot conclude that the formation of time-based task transition expectancy is dependent on the degree of predictability of interval–transition combination. This issue should be further investigated in future studies addressing time-based transition expectancy in task switching.

As already stated above, Bayesian analysis did not yield evidence for any difference of time-based transition expectancy between different degrees of predictability (90% in Experiment 4 and 80% in Experiment 5). Thus, any interpretations about the fact that time-based expectancy for task type was observable across different degrees of predictability (ranging from 90% in Experiment 1 to even 70% in Experiment 3), but time-based expectancy for task transition was only observable for a rather strong degree of predictability of 90% (Experiment 4) should be considered with caution. One interpretation might be that mere transition cueing reflects higher demands for endogenous control in contrast to cueing the task type itself (see Forstmann et al., 2005). By using fMRI, Forstmann et al. (2005) compared different degrees of endogenous control by introducing two different types of cues: Transition cues informed participants to switch or to repeat a task without being directly linked to a task set. In contrast, task cues told the participants directly which task they had to perform in the current trial. For transition cueing, Forstmann and colleagues (2005) found a frontomedian activation indicating a higher cognitive demand for endogenous control in comparison to direct task cueing. Please note that Forstmann and colleagues (2005) compared *explicit* task cueing with *explicit* transition cueing. However, time-based predictability can be rather seen as an *implicit* cueing procedure for both task types and task transitions. Thus, it remains questionable to what degree the results of Forstmann et al. (2005) can be transferred to the present study. As the task set is not directly triggered by a direct cue-task association, neither in time-based expectancy for task type, nor in time-based expectancy for task transition, future studies on time-based expectancy in the task-switching paradigm should take a closer look at the internal cognitive preparatory processes involved in time-based expectancy of task type on the one hand and time-based expectancy of task transition on the other hand.

Furthermore, in Experiments 1 through 3 time predicted the upcoming task, but as only two different tasks were used in the present study, it is not yet clear whether participants expected the task set itself or rather indirectly a task switch, respectively a task repetition. The same holds true for Experiments 4 and 5. When the time interval predicted, for example, a task switch in Experiments 4 and 5, it was (at least implicitly) clear that the other task would appear most likely in the current trial. Thus, on the basis of the present findings, no conclusion can be drawn concerning the actual target of expectancy in the present experiments. Did participants expect the task set itself—directly when task was predictable, and indirectly when transition was predictable? Or did they rather expect transitions—directly when transition was predictable, and indirectly when task was predictable? Or did they expect task when task was predictable and transition when transition was predictable? To investigate whether time-based expectancy for task type and time-based expectancy for task transition are really independent forms of expectancy in the task-switching paradigm, future studies should employ three tasks instead of two. In this manner, a time-based prediction of the upcoming task transition would give no clear hint about the identity of the upcoming to-be-performed task in the current trial. If the time-based expectancy effect for task transition would still be observable in this case, this result would clearly speak in favor of an expectancy for an abstract task transition.

In all reported experiments (except Experiment 5), participants responded faster in trials with the short interval of 500 ms compared to trials with the long interval of 1,500 ms. This result pattern was independent of task transition (repetition or change), or of type of expectancy (task expectancy in Experiment 1–3, or transition expectancy in Experiment 4,5). This finding was unexpected, because previous studies using the time-based correlation paradigm found the opposite pattern (see Wagener & Hoffmann, 2010, and Introduction). One potential explanation for the unexpected finding draws on phasic alertness. There are a few studies from the field of task switching which employed neutral warning signals prior to cue onset to investigate effects of unspecific temporal preparation (Meiran et al., 2000). The observed effects were only weak, and Meiran et al. (2000) attributed these effects to stimulus-induced shifts of phasic alertness. This alertness might have been effective with short intervals in the present study, but might have decayed at the longer interval. However, it should be noted that the finding of faster RTs after short than after long pretarget intervals could be also related to classical effects of time uncertainty, which means the participant's imperfect time keeping ability during the course of an interval (cf. Klemmer, 1956; Näätänen, 1972).

The results of the present study show that time-based expectancy for task type and for task transition seems to improve performance in a task-switching scenario and that this time-based expectancy effect seems not to be switch-specific as performance benefits for frequent combinations of interval and task type (Experiments 1 through 3), respectively task transition (Experiment 4) occurred in both—switch trials and repetition trials. This finding was further supported by Bayesian analysis which revealed evidence in favor of the null-hypothesis (no difference of time-based expectancy in switch and repetition trials) both for time-based task expectancy (Experiment 1–3) and time-based transition expectancy (Experiment 4, 5). Please note that the present experiments do not allow to conclude that a task-specific preparatory process took place during the pretarget interval. As the target color (i.e., the explicit task cue) was always predictable to the same degree as the task itself, the time-based expectancy effect could have reflected efficiency of cue processing. The issue whether the time-based expectancy effect in task switching is due to a facilitation of perceptual processing of the target color or to a specific preparation process which takes place during the course of the pretarget interval should be investigated in future studies by employing two colors per task instead of one to dissociate between a perceptual cue expectancy and a specific expectancy of the task set. However, the results of the present study support the assumption that cognitive processes benefit from time-based expectancy, that take place in switch and repetition trials (see also Dreisbach et al., 2002; Koch, 2003, 2005). In this context, parallels can be drawn to studies on implicit sequence learning which typically also found that performance benefits from sequence-based predictability were equal for task repetitions and for task switches (Gotler et al., 2003).

Furthermore, in studies on implicit sequence-based predictability (Gotler et al., 2003) participants usually do not have any explicit knowledge about the implicit task sequences and also in the present study, participants in all five reported experiments had no explicit knowledge about the temporal regularities and therefore were not aware of the predictive value of the intervals. Nevertheless, at least in Experiments 1 through 4, participants formed time-based expectancies of task type (Experiments 1–3), and task transition (Experiment 4), and these expectancies seemed to have supported the cognitive processing of tasks. In case of a specific preparation during the pretarget interval, our results could therefore be seen as an extension of previous findings concerning implicit proactive control and would support the finding of Farooqui and Manly (2015) that

> such control can be based on information derived from aspects of the task environment outside awareness and conscious knowledge and that subliminal information can be utilized via associative learning even when there is no a priori plan for its use. (p. 332)

According to Farooqui and Manly (2015), this conclusion is of particular importance, as learning new, arbitrary relations (like in the present study the relation between interval duration and task type, or task transition) has been long time thought to require consciousness.

To our knowledge, the present study showed for the first time that humans can build time-based expectancies, when time predicts the upcoming task type or the upcoming task transition. It can be argued that time-based task predictability has some aspects in common with sequence-based designs, but others with cue-based designs. Like sequence-based predictability with longer implicit sequences, time-based preparation is usually implicit, in the sense that participants do not become aware of the predictability relation (Thomaschke et al., 2015). On the other hand, time-based task predictability can be seen as an instance of cue-based task predictability, because interval duration can be seen as a cue in this context.

However, the cognitive processes underlying time-based expectancy in task switching are not yet clear. For example, it has been suggested that encoding of the task cue plays an important role in understanding cognitive processing in task-switching situations (Logan & Bundesen, 2003; Mayr & Kliegl, 2003). As already stated above, the task always coincided with the explicit task cue (i.e., the color of the target stimulus) and thus any effect of task predictability might have been due to cue predictability. We recommend that future studies dissociate between perceptual cue expectancy and time based expectancy of the task set (which would imply a specific preparation process during the course of the pretarget interval). Further, due to the increasing technical mediation of almost every interaction environment (Livingstone, 2009), the temporal predictability of delays has become technically controllable by temporal scheduling of system response delays (Thomaschke & Haering, 2014). Thus, a deeper understanding of the effects of time-based task expectancy and the related underlying cognitive mechanisms would have direct implications for the optimization of technically mediated multitasking environments.

Conclusion

The present study demonstrated for the first time that participants are able to form time-based expectancies in the task-switching paradigm when time predicts the task type or the task transition in the upcoming trial. Whereas previous studies in task switching manipulated the time interval prior to stimulus onset, typically to investigate task preparation, and found for example reduced switch costs on the basis of prolonging the response-stimulus interval or the cue-stimulus interval (Meiran, 1996; Rogers & Monsell, 1995), our findings show for the first time that participants benefit not only from long preparation intervals, but that the predictive value of these intervals' duration plays a crucial role for the cognitive processing of tasks in task switching. The performance benefit on the basis of time-based expectancy in task switching was observed in both switch trials and repetition trials and thus seems to be not switch-specific. However, to gain a full understanding of the cognitive processes underlying human performance in task switching, it is essential to establish in future studies how time-based expectancy for task type and for task transition is exactly processed.

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