# Time-based event expectations employ relative, not absolute, representations of time 

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#### Abstract

When the timing of an event is predictable, humans automatically form implicit time-based event expectations. We investigated whether these expectations rely on absolute (e.g., 800 ms ) or relative (e.g., a shorter duration) representations of time. In a choice-response task with two different pre-target intervals, participants implicitly learned that targets were predictable by interval durations. In a test phase, the two intervals were either considerably shortened or lengthened. In both cases, behavioral tendencies transferred from practice to test according to relative, not absolute, interval duration. We conclude that humans employ relative representations of time periods when forming time-based event expectations. These results suggest that learned time-based event expectations (e.g., in communication and human-machine interaction) should transfer to faster or slower environments if the relative temporal distribution of events is preserved.


Keywords Human associative learning • Cognitive and attentional control $\cdot$ Implicit learning and memory $\cdot$ Motor control

Temporal cognition is currently a rapidly growing area of research in the behavioral sciences and neuroscience (Merchant, Harrington, \& Meck, 2013; Simen, Balci, deSouza, Cohen, \& Holmes, 2011; Wittmann, 2013). The cognitive ability to process duration is essential to anticipatory behavior because many behaviorally relevant environmental events occur in a temporally predictable manner. Temporal cognition

[^0]supports anticipatory behavior in two different ways (Thomaschke, Wagener, Kiesel, \& Hoffmann, 2011c): time expectancy and time-based event expectancy.

Time expectancy can be defined as the anticipation of an interval's expiration time. The mechanisms of time expectancy have mostly been studied with the foreperiod paradigm, in which the duration between a warning signal and a target signal (the foreperiod) is manipulated (Los \& Agter, 2005; Schröter, Birngruber, Bratzke, Miller, \& Ulrich, 2014; Woodrow, 1914). A robust finding in the foreperiod paradigm is that when foreperiods are randomly intermixed, response time (RT) increases monotonically with warning interval duration. Two explanations for this effect have been discussed in the literature. Some authors have suggested that the reduction in RT might be due to the monotonous increase of conditional probability of immediate stimulus occurrence during more and more potential presentation times passing by (Elithorn \& Lawrence, 1955; Janssen \& Shadlen, 2005; Leon \& Shadlen, 2003). Others have proposed an explanation in terms of sequential priming effects (Los, Knol, \& Boers, 2001; Steinborn, Rolke, Bratzke, \& Ulrich, 2008).

Time-based event expectancy, on the other hand, is the expectancy for an event based on the passage of time. Consider, for example, how our event expectancy changes while waiting for a Web page to load. As time elapses, we go from expecting successful loading to expecting an error message (Seow, 2008). Fundamental research on time-based event expectancy has typically applied a certain variant of the foreperiod paradigm - namely, the time-event correlation paradigm (Wagener \& Hoffmann, 2010b). In this paradigm, two targets and two interval durations are both equally probable, but, crucially, the combinations of interval and target differ in probability. While occurrences of one target are preceded by the shorter interval $80 \%$ of the time, occurrences of the other target are preceded by the longer interval $80 \%$ of the time. Time-based event expectation leads to faster responses to
frequent interval-target combinations, relative to infrequent ones (Thomaschke, Wagener, Kiesel, \& Hoffmann, 2011b; Wagener \& Hoffmann, 2010b). As with time expectancy (see above), some studies suggest that time-based event expectancy gets more pronounced with longer, rather than shorter, intervals (Thomaschke \& Haering, 2014; Thomaschke, Wagener, et al., 2011b).

An important and as yet unanswered question about timebased event expectancy is whether the expectancy is based on absolute (e.g., 600 ms ) or relative (e.g., the shorter of two intervals) representations of time. Both kinds of representa-tions-absolute and relative-have previously been demonstrated in several domains of human timing. Examples of evidence for absolute duration representations come from temporal learning studies. These studies show that, for explicit interval production and discrimination, extensive training with a certain interval generalizes only to a relatively narrow duration range, while performance with other durations remains unaffected (Bartolo \& Merchant, 2009; Meegan, Aslin, \& Jacobs, 2000; Nagarajan, Blake, Wright, Byl, \& Merzenich, 1998; Wright, Buonomano, Mahncke, \& Merzenich, 1997). Other cognitive capacities employ relative durations. Kunde (2003), for example, has shown that duration representations are involved in ideomotor processes (i.e., processes integrating anticipated effects into action choice). These processes are known to operate exclusively on categorical (nonmetric) representations (see Thomaschke, Hopkins, \& Miall, 2012a, 2012b). Others have demonstrated that relative duration representations are employed when humans explicitly classify intervals (e.g., Molet \& Zentall, 2008) and when several nonhuman species temporally schedule overt behaviors (Church \& Deluty, 1977; Zentall, 2007; Zentall, Weaver, \& Clement, 2004; but for a different view, see de Carvalho \& Machado, 2012; Spínola, Machado, de Carvalho, \& Tonneau, 2013).

In the present article, we investigate which one of these time representations - absolute or relative - is involved in time-based event expectancy. To this end, we integrate two methods previously employed in different areas of timing research. On the one hand, previous studies have demonstrated that time-based event expectancy is relatively stable. Once time-based event expectancy has been acquired by adaptation to time-event correlation, it is still effective even when, in the current environment, events are not temporally predictable anymore (Rieth \& Huber, 2013; Thomaschke \& Dreisbach, 2014). On the other hand, previous learning studies have tested whether learning of temporal discrimination skills, or of timed behavior, transfers to unlearned duration ranges (Mendez, Prado, Mendoza, \& Merchant, 2011; Zentall, 2007). Transfer is typically interpreted as evidence for relative representations (Molet \& Zentall, 2008), while duration specificity is commonly interpreted as evidence for absolute representations.

In the present study, we combine both strategies. In a learning phase, participants adapt to a time-event correlation
of $80 \%$. In a following test phase, two changes are introduced: First, the time-event correlation becomes neutral (50\%); second, the warning intervals change to a new duration range. In one group, the pair of intervals changes from shorter (200 and 800 ms ) to longer ( 800 and $1,400 \mathrm{~ms}$ ), while in another group it changes from longer to shorter.

If participants learn to build their time-based event expectancy according to relative duration, the expectancy should generalize, in relative terms, from the learning to the test phase. Participants should expect one event at the shorter interval and the other event at the longer interval, irrespective of the current duration range. Above that, we expect timebased event expectancy to be more pronounced at longer than at shorter intervals (see above). However, if time-based event expectancy is based on relative duration representation, this asymmetry should be independent of absolute duration and should, consequently, be present in the short, as well as in the long, pair of intervals.

## Method

## Participants

We tested two groups of 10 participants each; 15 were female, 7 were left-handed, and the mean age of participants was 23.68 years $(S D=6.01)$. One participant was excluded from the analysis due to an exceptionally high error rate (19.4\%).

Procedure

## Task

Participants performed a binary choice response task presented as a basic computer game. They controlled a stylized donkey chasing a stylized carrot, which moved repeatedly from bottom to top of the screen in a zigzag, left-to-right course (see Szameitat, Rummel, Szameitat, \& Sterr, 2009, for a detailed description of a similar procedure). At each step, the carrot moved in an upward direction, diagonally left, or diagonally right. When the carrot jumped to the left, participants had to press the left mouse button in order to make the donkey follow the carrot leftward (pressing the right mouse button moved the donkey to the right). After the mouse click, the donkey immediately jumped on the carrot. After a short or long variable interval (see below), the carrot jumped away again. After six steps, the carrot reached a stylized fence at the upper border of the screen, at which point it could jump no farther, and a "carrot counter" in the upper right corner of the screen was incremented. One experimental block consisted of 25 carrot chases, each chase being composed of six jumping steps. When participants pressed the wrong key or pressed the key before the carrot had jumped, an error message was
displayed, an aversive tone was played over the headphones, and the game was paused for 3 s .

## Predictive intervals

In each block, the response-stimulus interval (i.e., from mouse click to carrot movement) varied randomly between two possible durations. However, during a four-block practice phase, the interval duration predicted the carrot's next movement direction with $p=.8$, while in a one-block test phase the direction was unpredictable, $p=.5$. The pairing of duration and direction in the practice phase was counterbalanced across participants.

One group (the upshift group) practiced with a 200-/800ms interval pair and was tested with an $800-/ 1,400-\mathrm{ms}$ pair. This order was reversed for the other group (the downshift
group; see Fig. 1). Participants were not informed about the interval-direction correlation. After the experiment, participants completed a questionnaire, which asked them whether they had detected any temporal regularity in the experiment.

## Results

We analyzed data from the test phase and from the last block of the practice phase. Trials following error trials and the initial trial in each block were excluded from the analysis. Error trials and trials with RTs deviating from the condition mean by more than three standard deviations were excluded from the RT analysis (Bush, Hess, \& Wolford, 1993). We

## Upshift group



Block 5: test


## Downshift group



Fig. 1 Mean response times (RTs) in the practice phase (left panels) and test phase (right panels), depending on interval duration and target. Error bars represent 1 standard error of the mean. Asterisks denote significance in a $t$-test with a significance level of .05
calculated mean error rates and mean RTs for each combination of interval and response (see Fig. 1).

We conducted a mixed analysis of variance (ANOVA) with the between-subjects factor of group (upshift vs. downshift) and the within-subjects factors of phase (practice vs. test), interval (short vs. long), and frequency (frequent vs. infrequent target-interval combination). Note that in the test phase, "frequency" was coded according to the current target-interval combination's previous frequency (i.e., whether it had been frequent in the practice phase) and that this coding was done in relative terms. A combination with the currently shorter interval in the test phase was coded as "frequent" when the current target had been frequent with the previously shorter interval in the practice phase.

Overall, participants responded more slowly to short (367 $\mathrm{ms}, S D=53)$ than to long ( $336 \mathrm{~ms}, S D=51$ ) intervals, $F(1$, 17) $=26.124, p<.001, \eta_{\mathrm{p}}^{2}=.606$. We also observed a main effect for frequency, $F(1,17)=21.775, p<.001, \eta_{\mathrm{p}}^{2}=.562$, due to faster responses to frequent combinations ( 343 ms , $S D=53$ ) than to infrequent combinations ( $366 \mathrm{~ms}, S D=48$ ). Frequency interacted with phase, $F(1,17)=6.737, p=.019$, $\eta_{\mathrm{p}}^{2}=.284$. The advantage of frequency was larger in the practice phase, $t(18)=4.727, p<.001$, Cohen's $d=1.04$, $\lambda=0.005,{ }^{1}$ than in the test phase, $t(18)=3.723, p=.002$, $d=0.82, \lambda=0.041$. Frequency also interacted with interval, $F(1,17)=7.828, p=.012, \eta_{\mathrm{p}}^{2}=.315$. A numeric advantage for frequent combinations over infrequent ones was not significant for the short interval, $t(18)=1.207, p=.243, d=0.27, \lambda=2.91$, but was for the long interval, $t(18)=5.130, p<.001, d=1.13$, $\lambda=0.002$. No other main effect or interaction was significant, all $F \mathrm{~s}<2.65$, all $p \mathrm{~s}>.121$. In an analogous ANOVA for error rates, no main effect or interaction attained significance. None of the participants reported having detected the manipulated temporal regularity in the postexperimental questionnaire.

## Discussion

We investigated whether time-based event expectations were based on absolute or relative representations of time. We trained human participants to associate two choice-responses to different interval durations. In a test phase, we shifted the duration of the intervals up or down and eliminated the re-sponse-interval correlation. Results clearly speak in favor of relative representation. First, interval duration interacted with frequency of combination, indicating that time-based event expectancy was more pronounced with longer intervals. Crucially, this interaction was not modulated by group and phase,

[^1]showing that time-based event expectancy was restricted to the relatively longer interval of the current pair of intervals, irrespective of its absolute duration. This means expectancy was formed for 800 ms in the upshift group but for $1,400 \mathrm{~ms}$ in the downshift group.

Second, time-based expectancy transferred to the test phase according to relative representation. At the new longer interval, participants in both groups responded significantly faster to the target that had been frequent at the previous longer interval. However, an interaction between phase and frequency showed that the behavioral tendencies acquired in the practice phase showed some decay when participants adapted to the new, neutral correlation in the test phase. From the results of both experimental phases, we concluded that humans employ relative, not absolute, representations of time when developing time-based event expectations.

Despite providing clear evidence concerning the representational coding of duration in time-based event expectancy, our study leaves open another essential question about the mechanisms underlying time-based expectancy. The present experiment is not informative about the cognitive processes that actually benefit from time-based event expectancy. Several subprocesses involved in responding to a stimulus have been shown to benefit from prior information, such as perceptual identification (Posner, 1980) or motor processing (Leuthold, Sommer, \& Ulrich, 1996; Rosenbaum, 1980). Previous studies have investigated which of these processes is primarily responsible for the behavioral benefits of time-based expectancy. Wagener and Hoffmann (2010a), for instance, observed a more pronounced time-based expectancy effect with multimodal target stimuli and concluded that timebased event expectancy affects primarily perceptual processes. Other studies have shown that time-based event expectancy is specific to the response hand (Thomaschke \& Dreisbach, 2013), but not to visual aspects of the stimulus (Thomaschke, Kiesel, \& Hoffmann, 2011a), suggesting that primarily motor processes benefit from time-based event expectancy. There is an analogous debate about the effects of unspecific time expectancy, with some authors showing perceptual (Rolke, 2008; Seibold, Fiedler, \& Rolke, 2011) and other motor aspects (Tandonnet, Garry, \& Summers, 2010) to benefit from expectancy. However, in the present study, motor, as well as perceptual, explanations of time-based expectancy are possible.

In addition to providing information about the basic cognitive mechanism underlying time-based event expectations, our study has practical implications because time-based event expectations are prevalent in many types of interaction envi-ronments-for example, in verbal communication (Roberts \& Francis, 2013; Roberts, Margutti, \& Takano, 2011; Watanabe, Hirose, Den, \& Minematsu, 2008) and human-machine interaction (Shahar, Meyer, Hildebrandt, \& Rafaely, 2012; Thomaschke \& Haering, 2014). The fact that we base our
event expectations on relative time intervals (e.g., after relatively short intervals, we expect the Web page to load successfully; after relatively long intervals, we expect an error message) means that our time-based event expectations generalize to environments that are globally and consistently slower or faster, if the relative timing is preserved (e.g., when switching from browsing the Internet with high-speed access to mobile G3 access, or vice versa).

It is, however, not clear from the present experiment which role metacognitive processes play in this generalization. Whether individuals build time-based event expectancies according to relative or to absolute interval representations might depend on their implicit or explicit assumptions about the temporal structure and stability of the current interaction environment. When individuals assume their interaction environment to be susceptible to global timing changes, as with, for example, transmission-rate sensitive Web-based computing applications, they might tend to form relative time-based event expectancies, because these expectancies would still be useful after global slowing or speeding. When, on the contrary, an environment can be assumed to be temporally invariant, such as when interacting with simple mechanical devices, individuals might form expectancies based on absolute intervals, because such expectancies allow more precise preparation. In the procedure of the present study, we did not intentionally induce assumptions about the temporal structure and dynamics of the computer program (i.e., the introduction of new intervals in Block 5 was not mentioned in the instructions). However, global slowing or speeding is a prevalent experience when interacting with computers-for example, when entering a new level in a computer game or when processor resources are consumed or released by another concurrent process or user. Such experiences might have biased participants to form relative instead of absolute representations of time.

Another potential bias toward relative duration representations might come from the binary nature of our design. The use of only two intervals in each experimental phase could have encouraged participants to categorize the intervals into "short" and "long" and, hence, to form relative temporal expectations. In scenarios with more than two intervals, participants might have been less biased to represent expectancies according to relative duration. We suggest that further empirical research attempts to determine the generalizability of the present finding to other interaction contexts and ranges of potential interval durations.

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[^1]:    ${ }^{1} \lambda$ estimates the Bayesian odds in favor of the null hypotheses, according to Rouder, Speckman, Sun, Morey, and Iverson (2009). Cohen's $d$ has been standardized by difference scores, because the design is inherently within subjects (Gibbons, Hedeker, \& Davis, 1993).

