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# A Walk Down the Lane Gives Wings to Your Brain. Restorative Benefits of Rest Breaks on Cognition and Self-Control

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*Summary: We investigated the effect of rest breaks on mental-arithmetic performance, examining performance as a function of the factor rest, time-on-task, and demand. We asked the following questions: (i) Does rest (vs a continuous-work condition) improve cognitive performance? (ii) Is active rest (taking a walk) better than passive rest (watching a video)? (iii) Do compensatory effects of rest increase with time-at-work? (iv) Are there differential effects of rest on automatic and controlled processes? (v) Are there differential effects of rest on performance speed versus variability? The results indicate that while rest is generally beneficial for performance, these benefits are similar for active and passive rest. The benefits increase with time-on-task and are larger for high (vs low) demand. Further, the effects on average response speed originated only partially from a reduction in the probability of attentional failure, as indicated by reaction-time (ex-Gaussian model) distributional and delta-plot analysis.*

It is a truism that rest improves cognitive efficiency. In fact, no one today would dispute the idea that cognitive efficiency at school or at work is subject to variations which might be overcome by taking a rest in order to restore attentional resources or simply to get some distance from currently performed activities. However, as soon as one goes into the details of how exactly rest affects cognition, such former consent rapidly diminishes and might even reverse into severe disagreement. For example, one could claim that taking a walk around the street is more restful than to take a rest in stillness, but conversely, one could also claim the opposite. Kahneman (2013, p. 39) positions himself as someone who prefers active over passive rest, by stating: '…*I have found a speed*, *about 17 minutes for a mile*, *which I experience as a stroll. I certainly exert physical effort and burn more calories at that speed than if I sat in a recliner*, *but I experience no strain*, *no conflict*, *and no need to push myself. I am also able to think and work while walking at that rate. Indeed*, *I suspect that the mild physical arousal of the walk may spill over into greater mental alertness*…'. Here, we examined the effect of rest on performance in self-paced mental arithmetic.

## HISTORICAL BACKGROUND: EFFECTS OF REST ON MENTAL EFFICIENCY

Since the end of the 19th century, researchers began to assess the efficiency of human performance by means of chronometric [reaction time (RT)-based] methods to infer to the duration or fluctuations of cognitive operations. While some researchers were particularly interested in the speed of mental processes, considering fluctuations as measurement artifact (Peak & Boring, 1926), others were precisely interested in this latter aspect, theorizing on the causes and underlying mechanisms of performance fluctuations (Robinson & Bills, 1926). The observed intraindividual variations in RT performance were attributed to an accumulation of refractory-phase effects originating from the permanent overuse of mental operations, and thus indicating the need for recuperation (Dodge, 1917; Poffenberger, 1928; Robinson & Bills, 1926; Weaver, 1942). One of the great pioneers at this time, Kraepelin (1902), developed the famous work curve, requiring individuals to engage in continuous mental addition for a prolonged time period. He suggested two primary sources of performance fluctuations: accumulation of short-term fatigue (refractoriness) and effort (motivational) variations and further observed that taking short rest breaks counteract these effects.

Since the classic work of Bills (1931, 1935), the occasional appearance of extra-long reaction times (mental blocks) during self-paced decisions has been considered one of the most sensitive criteria of short-term fatigue. Bills (1931, 1935) did not analyze the entire RT distribution but defined mental blocks operationally as responses longer than twice the individual mean within a series of trials. He considered it almost certain that mental blocks act as enforced micro rest that is inherent in the cognitive system to prevent a more severe decrement from occurring. Bills (1931, p. 244) stated that '…*the rest afforded by these blocks keep the individual's objective efficiency up to an average level*…'. Bertelson and Joffe (1963) administered their participants with a self-paced four-choice task that lasted for about 30 min, requiring them to press one of four keys mapped onto one of four digits (1–4). Their result also indicates that mental blocks enforce rest to ensure efficient performance afterward. While blocks were preceded by a slowing of response and a decline in accuracy, they were followed by a sudden improvement in both measures (cf. Bertelson & Joffe, 1963, Figure 4). Thus, one might reason whether explicitly administered rest reduces block frequency.

Sanders and Hoogenboom (1970) administered their participants with a six-choice RT task (response-stimulus interval = 60 ms), either a continuous work or a rest-break condition. The digits 1–6 served as targets and were mapped onto six separate keys. Responses became faster on average

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in the rest-break condition, while they remained the same in the continuous-work condition. Moreover, a cumulative distributive function (CDF) analysis revealed that both conditions did not differ with respect to the fastest but only the slowest CDF percentiles. Sanders and Hoogenboom (1970) interpreted their results, such that rest breaks proactively prevent mental blocks from occurring, and by this means, reduce response-speed variability. This interpretation is in agreement with earlier proposals. For example, Jersild (1926, p. 34) observed that his participants committed occasional attentional failure in speeded color naming which he termed as '…*thwarted mental activity*…', indicating that the (verbal) response-selection process '…*seems to lag behind the immediate perceptual process*…'. Taken together, today's researchers are endowed with an abundance of findings, although the diversity of terms and language use and the lack of theoretical formalism in earlier studies make it difficult to directly derive clear predictions from this literature.

## THEORETICAL BACKGROUND: SPARE–UTILIZED CAPACITY MODEL

The present research deals first of all with the effects of brief rest on performance in active sustained-attention tasks, sometimes termed self-paced speeded tests (Pieters, 1985; Van Breukelen et al., 1995). In these tests, individuals have to attain and to maintain response activation and mental focus over a (more or less) prolonged period of time (Steinborn, Flehmig, Westhoff, & Langner, 2008; Steinborn et al., 2010). According to Langner and Eickhoff (2013), it is important to distinguish between active and passive sustained-attention tasks (i.e., self-paced tasks vs vigilance tasks) in order to avoid confusion when theorizing about the underlying cognitive mechanisms. This might particularly be important with respect to overall performance, with respect to the ubiquitous performance decrement, as well as with respect to its compensation by rest breaks (Ariga & Lieras, 2011; Helton & Russell, 2015). To approach this question, let us take the simplest example of a self-paced mental-arithmetic task where individuals have to verify whether a presented addition term (e.g., $2+3=5$) is correct or incorrect. According to Kahneman (1973), the processes involved in active mental operations such as addition and subtraction can be regarded as mobilization and permanent deployment of mental effort to task operations.

The crucial assumption of a spare–utilized capacity model is that there is a global limit on individuals' capacity to perform a task, which can be devoted either to active task operations or to monitoring. Kahneman (1973) suggested that the control over the allocation policy is to merely set up global priorities, while the dynamic allocation of effort during the task depends on the actual demands. Crucial to such a view is the distinction between utilized and spare capacity. Capacity is never fully utilized for algorithmic mental operations, but there is always some spare capacity left to monitor whether performance standards are met. Importantly, the amount of capacity is not constant but depends on current needs. An increase in demand immediately yields a mobilization of capacity through an increase in arousal. This means that the ratio of utilized versus spare capacity is under continual evaluation and re-adjustment of priorities toward sustainable performance. Thus, the extent to which the cognitive system uses the capacity potentially available for current task processing varies over a period of mental work. In this way, performance stability depends on the capacity that an individual continuously deploys to the task, and performance variability is attributed to effort variations (cf. Stuss et al., 2005, pp. 397–398).

An energetic view of sustained attention in active work tasks implies the following question: What exactly makes rest breaks effective with regard to their ability to improve performance (or to prevent its deterioration) as compared with a continuous-work condition in active tasks? Any variation in the effort deployed to the active cognitive operations occurs, according to Kahneman (1973), because the allocation policy sometimes channels available capacity to other activities. These other activities might be relevant to the task at hand or entirely irrelevant. Thus, while prolonged mental work decreases the capability to deploy attention to active mental operations relative to (more passive) monitoring processes, rest is predicted to restore this capability. Formally, prolonged work affects the spare–utilized capacity ratio by increasing spare over utilized capacity, while rest restores the correct (optimal) ratio by increasing utilized over spare capacity. Thus, rest is predicted to counteract suboptimal levels of arousal, and thus to maintain stability of performance (Hockey, 1997; Humphreys & Revelle, 1984). Although there are some clues in the literature, a more profound distributional and delta-plot analysis is necessary to explicitly support such a position (De Jong, Liang, & Lauber, 1994; Ridderinkhof, 2002; Steinborn, Langner, Flehmig, & Huestegge, 2016).

## PRESENT STUDY

Here, we examined the effects of brief rests on performance in active work tasks, sometimes termed self-paced speed tests (Van Breukelen et al., 1995), by studying the effects of rest breaks, time-on-task (TOT), and central demand on performance. We asked the following questions: (i) Does rest improve performance? (ii) Is active rest (taking a walk) better than passive rest (watching a video)? (iii) Do compensatory effects of rest (relative to non-rest) increase with time-at-work? (iv) Are there differential effects of rest on automatic and controlled processes (low vs high mental-arithmetic demand)? (v) Are there differential effects of rest on performance speed versus performance variability? Although previous findings addressed related phenomena, that is, differential effects of rest versus task changes on performance (e.g., Helton & Russell, 2012; Ross, Russell, & Helton, 2014), our question has not sufficiently been addressed. Note that TOT effects in mental-arithmetic do not necessarily produce a global response slowing but might also be subject to procedural learning (Compton & Logan, 1991; Zbrodoff & Logan, 1990). Also, fatigue might affect these processes differently at different points in practice (Healy, Kole, Buck-Gengler, & Bourne, 2004; Healy, Wohldmann, Sutton, & Bourne, 2006).

## METHOD

### Participants

A sample of 68 (58 women) normal volunteers (mean age = 21.7 years, $SD = 5.7$) was tested. One participant refused to finish the experiment and was excluded from the sample. Another one did not completely fill out the questionnaire.

### Apparatus and stimuli

The experiment was programmed using Psychopy (Peirce, 2009). The participants sat about 60 cm in front of the screen. We used a version of the mental-addition and verification tasks (Zbrodoff & Logan, 1990), using a response-stimulus interval of 50 ms. In each trial, an addition term together with the result is presented, and the participants indicated whether the result is either correct or incorrect. They were instructed to verify a correct result by pressing the right key (right index finger) and to falsify an incorrect result by pressing the left key (left index finger). The task contained easy and difficult items differing with respect to the chain length. Items categorized as easy included only simple additions (e.g., $4+5=9$; $4+5=8$), while items categorized as difficult included chained additions (e.g., $4+5+1+2=12$; $4+5+1+2=11$). There were 24 easy and 24 hard items. Each item was presented randomly and equally often (total of 900 trials).

### Self-report measures

Self-report measures were administered before and after the experiment. The Dundee Stress State Questionnaire (DSSQ), developed by Matthews et al. (2002), assesses the three fundamental dimensions of subjective state (engagement, distress, and worry). It has successfully been applied to performance contexts (Helton, Funke, & Knott, 2014; Helton, Matthews, & Warm, 2009; Matthews et al., 2010). We used the short DSSQ (Helton & Naeswall, 2015) in the German version (Langner, Eickhoff, & Steinborn, 2011; Langner, Steinborn, Chatterjee, Sturm, & Willmes, 2010), consisting of 30 items on a five-point Likert-type rating scale.

### Design and procedure

We compared the two groups. The continuous-work group (baseline, 35 participants) was required to work through the entire test (900 trials) without a break, while the rest-break group (critical, 32 participants) was given the opportunity to take a 3-min break after 300 and after 600 trials. The break was either active or passive, consisting of either a 3-min walk or a 3-min watching of an educational (explainity) video (cf. Krauskopf, Zahn, & Hesse, 2012). During the passive rest, the participants remained in the room and watched the film on the same computer. During the active rest, the participants took an outdoor walk at moderate intensity (they were instructed to walk as they do normally). The order of conditions was counterbalanced, such that half of the rest-break group passed through the session, having first a walk and then a video, while the other half of this group passed though the session, having first a video and then a walk. The participants were instructed to respond quickly and accurately. Self-reports were collected before and after the experiment. Overall, the experiment lasted about 50 min.

## RESULTS AND DISCUSSION

### Data treatment

Incorrect responses (errors) and responses faster than 100 ms were regarded outliers. Note that because our hypotheses implied an analysis of the RT distribution, we only used a minimal trimming method by removing the three slowest reactions for each of the experimental conditions.

### Standard performance indices

For each of the experimental conditions, we computed the RT mean (RTM) to index average response speed and the RT coefficient of variation to index relative response-speed variability, according to the suggestion of Flehmig et al. (2007) and according to our own previous use of this method (Flehmig, Steinborn, Westhoff, & Langner, 2010; Steinborn et al., 2008; Steinborn et al., 2010; Steinborn et al., 2016). Error percentage indicated the rate of incorrect responses and served as a measure of response accuracy.

### Distributional analysis

We computed a vincentized (interpolated) CDF of responses with 19 percentiles, according to the suggestion of Ulrich, Miller, and Schroeter (2007) and current use of this method (e.g., Flehmig et al., 2010; Steinborn et al., 2016; Ulrich, Schroeter, Leuthold, & Birngruber, 2015). We asked whether rest affects the entire RT distribution by a parallel shift of all percentiles, or alternatively, by a selective shift of only the slowest CDF percentiles (indicating attentional lapses). To more directly account for effects of distributional shape (skewness), we also adopted an ex-Gaussian approach of RTs (Heathcote, Popiel, & Mewhort, 1991; Steinhauser & Huebner, 2009), according to the methodical rules provided by Lacouture and Cousineau (2008). Parameters $\mu$ and $\sigma$ can readily be interpreted as localization and dispersion (around $\mu$) indicators, while $\tau$ is sensitive to experimentally induced right-tail density accumulation effects (Steinborn et al., 2016).

### Standard (GLM) analysis

The design contained one between-subject factor ‘group’ (continuous vs rest) and the within-subject factors ‘demand’ (low vs high) and ‘TOT’ (bins 1–3, containing 300 trials each). Overall, response speed was not different for the continuous-work group and the rest-break group (main effect of rest on RTM, $F < 1$). The responses were faster for the low-demand (vs the high-demand) condition, as indicated by the main effect of demand on RTM [$F(1,65) = 819.0, p < .001$]. The responses became also faster over the experimental session, as indicated by the main effect of TOT on RTM [$F(1,65) = 146.3, p < .001$]. Crucially, the relative benefit of rest breaks (vs continuous work) increased over the task session, as indicated by the rest × TOT interaction effect on RTM [$F(2,130) = 6.2, p < .01$]. Moreover, this TOT-induced benefit of rest was differentially more pronounced for difficult (vs easy) mental arithmetic, as indicated by a rest × demand × TOT interaction effect on RTM [$F(2,130) = 5.6$, $p < .01$]. The effects of the relevant factors on RT and accuracy can be inspected visually in Figure 1 and statistically in Table 1.

### Distributional analysis (standard)

Figure 2 illustrates the rest-break (vs continuous) condition, producing an effect in a rather uniform fashion (approximately 20 ms for the low-demand condition and 200 ms for the high-demand condition). That is, although the RT distribution in the rest-break experimental condition becomes visually somewhat less skewed over the testing period (Figure 2), relative to that of the control condition, the effect is also present in the fast percentiles of the CDF, although to a lesser degree. Globally, the indices of distributional skewness are in correspondence with the visual pattern. Although mental-arithmetic demand and TOT separately produced an increase in distributional right-tail density, as indicated by a main effect of demand on the ex-Gaussian $\tau$ parameter [$F(1,65) = 233.4$, $p < .001$] and

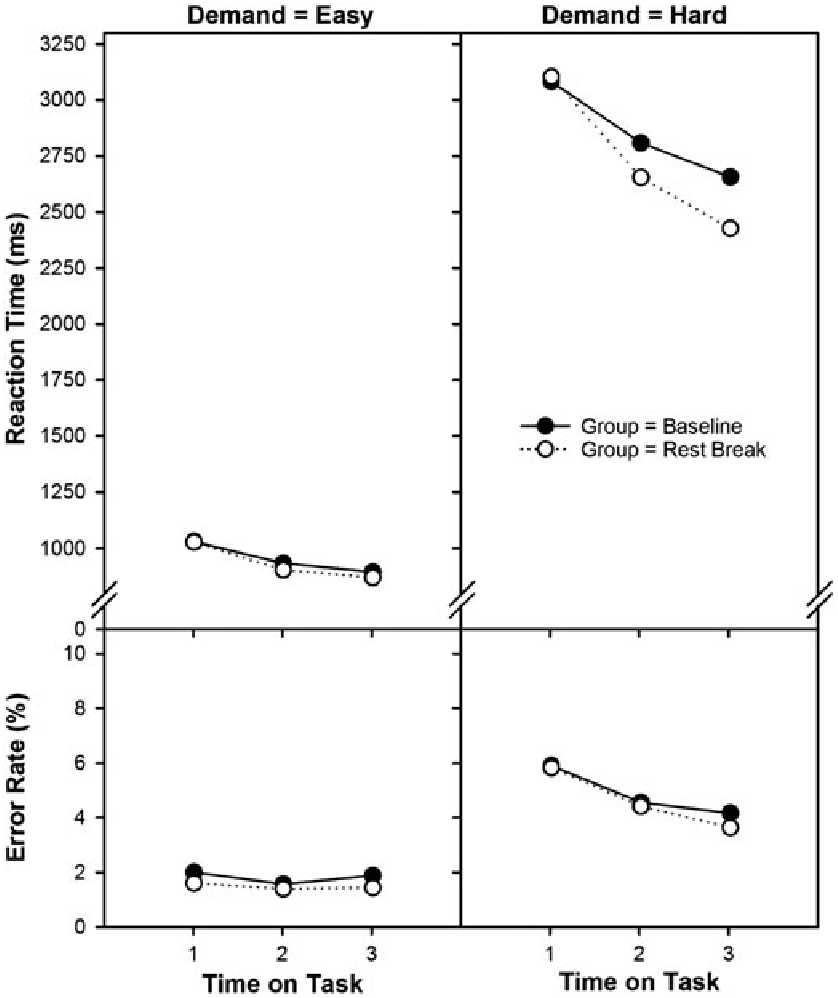

Figure 1. Reaction time mean and error percentage as a function of the factors 'rest' (continuous-work group vs rest-break group), 'demand' (easy vs hard), and 'time-on-task' (TOT: bins 1–3) in continuous mental-arithmetic performance

Table 1. Effects of rest breaks, demand, and time-on-task (TOT) on standard performance parameters

| Source | | | RTM | | | EP | | | RTCV | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *df* | *F* | *p* | $\eta^2$ | *F* | *p* | $\eta^2$ | *F* | *p* | $\eta^2$ |
| 1 | Rest (group) | 1.65 | 0.6 | .438 | 0.01 | 0.4 | .520 | 0.00 | 0.7 | .378 | 0.00 |
| 2 | Demand | 1.65 | 819.0 | .000 | 0.93 | 78.4 | .000 | 0.55 | 139.2 | .000 | 0.68 |
| 3 | TOT | 2.130 | 146.3 | .000 | 0.71 | 16.6 | .000 | 0.20 | 0.3 | .719 | 0.00 |
| 4 | Rest × Demand | 1.65 | 0.6 | .436 | 0.00 | 0.0 | .900 | 0.00 | 0.3 | .553 | 0.00 |
| 5 | Rest × TOT | 2.130 | 6.2 | .003 | 0.09 | 0.4 | .676 | 0.00 | 2.2 | .114 | 0.03 |
| 6 | Demand × TOT | 2.130 | 68.8 | .000 | 0.51 | 10.3 | .000 | 0.14 | 8.3 | .000 | 0.11 |
| 7 | Rest × Demand × TOT | 2.130 | 5.6 | .005 | 0.08 | 0.1 | .878 | 0.00 | 0.3 | .748 | 0.00 |

*Note*: Effect size: partial $\eta^2$; experimental factors: rest breaks (continuous-work group vs rest-break group), demand (easy vs hard mental-arithmetic condition), time-on-task (TOT, bins 1–3).

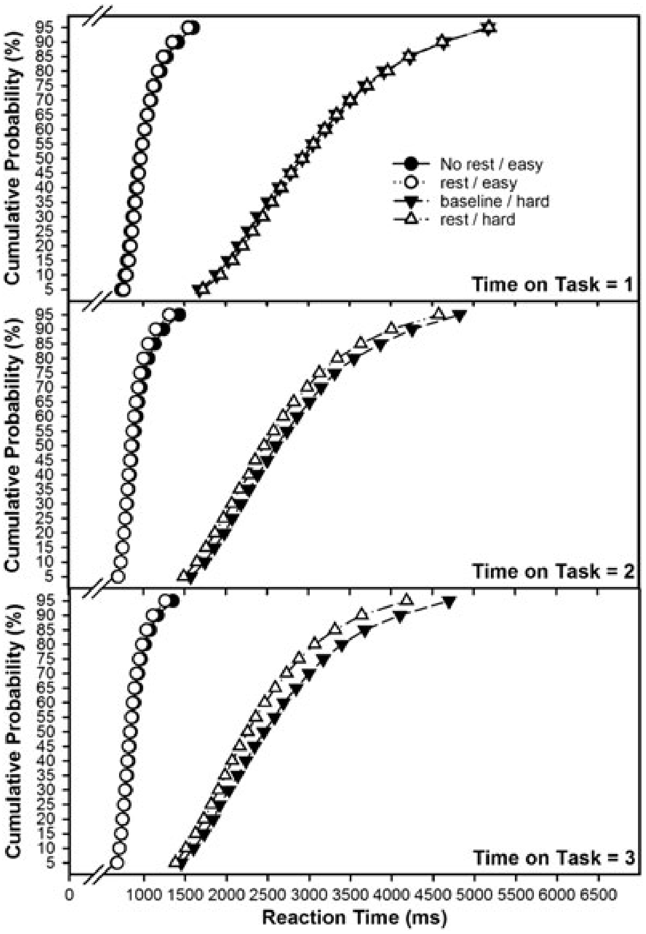

Figure 2. Vincentized cumulative distributive functions of reaction times for each combination of the factors 'rest' (continuous-work group vs rest-break group), 'demand' (easy vs hard), and 'TOT' in continuous mental-arithmetic performance

a main effect of TOT on the $\tau$ parameter [$F(1,65) = 6.1, p < .01$], there was neither a main effect nor an interaction effect related to the factor rest on this parameter (Figure 3, Tables 1 and 2).

### Self-report effects

Of interest was the question of whether these subjective states change across the session, in particular, whether subjective task engagement is relatively more affected in the continuous-work condition than in the rest-break condition (Hesse & Spies, 1996; Matthews et al., 2002). However, although exactly this is visually indicated (Figure 4), the results are not statistically significant (Table 3).

### Sequence analysis

The experimental setup enabled us to directly compare the effects of active and passive rest on performance, considering only the rest-break group. We compared the trial sequence surrounding rest breaks on performance (i.e., a pre–post comparison of the 100 trials before vs 100 trials after rest), comparably for the walk and the watch conditions. The GLM design contained the within-subject factors 'rest' (active vs passive), 'sequence' (before rest vs after rest), and 'demand' (low vs high). Crucially, there was a speed-up of responses after rest (vs before rest), as indicated by the main effect of sequence on RTM [$F(1,31) = 46.9$, $p < .001$], which was again relatively more pronounced for the high-demand (vs low-demand) condition, as indicted by the demand × sequence interaction effect on RTM [$F(1,31) = 35.1$, $p < .001$]. However, it seems not to matter whether the rest is taken in an active or passive form (Table 4, Figures 5 and 6).

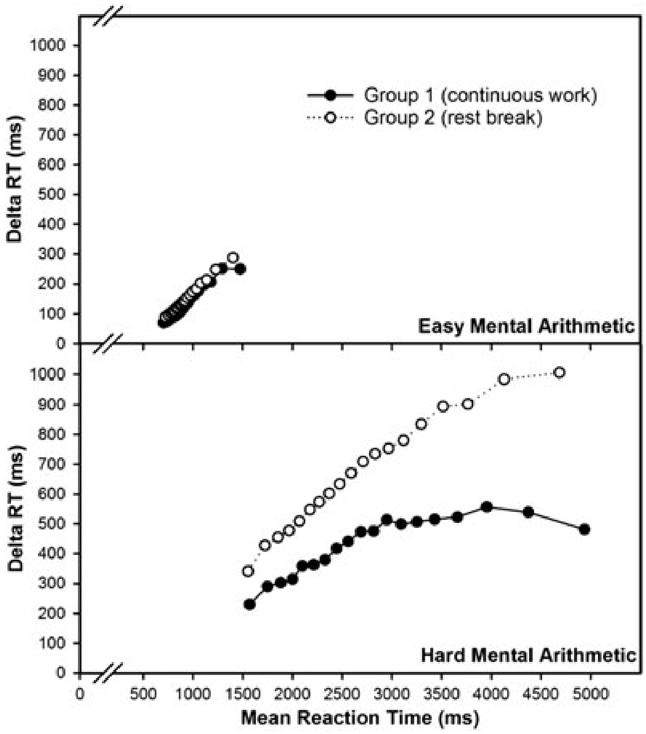

Figure 3. Delta plots of the 'TOT' effect. For each percentile, the real-time difference between the critical experimental conditions (TOT effect: bin 1 vs 3) is plotted against the mean of both conditions in that percentile, separately for the continuous-work group and the rest-break group

## DISCUSSION

We examined self-paced performance as a function of the factors 'rest', 'demand', and 'TOT'. In addition, we collected self-reports of subjective stress state before and after the experimental session, using the DSSQ. The results can be summarized as follows: Globally, rest breaks (vs no rest) are beneficial for performance as these benefits increase with increasing time at work. Importantly, the performance benefit related to rest is differentially more pronounced for hard than for easy mental arithmetic, and this effect of rest again increases with time at work. In contrast to previous studies, rest did not solely reduce the frequency of lapsing (or mental blocks, respectively), as would be indicated by a decrease in distributional skewness, but affected responses from the 19th percentile down to the 10th percentiles of the CDF. At a subjective level, there was a tendency indicating that rest retains task engagement (motivation). Finally, whether rest is taken in an active (by taking a walk) or passive (watching a video) fashion seems not be as important as one might think.

Table 2. Effects of rest breaks, demand, and time-on-task (TOT) on ex-Gaussian model parameters

| Source | | | μ (Mean) | | | σ (Variability) | | | τ (Skewness) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *df* | | | *F* | *p* | $\eta^2$ | *F* | *p* | $\eta^2$ | *F* | *p* | $\eta^2$ |
| 1 | Rest (group) | 1.65 | 0.1 | .740 | 0.00 | 0.8 | .386 | 0.01 | 0.7 | .386 | 0.01 |
| 2 | Demand | 1.65 | 778.0 | .000 | 0.92 | 269.3 | .000 | 0.81 | 233.4 | .000 | 0.78 |
| 3 | TOT | 2.130 | 153.0 | .000 | 0.70 | 35.4 | .000 | 0.35 | 6.1 | .003 | 0.09 |
| 4 | Rest × Demand | 1.65 | 0.4 | .550 | 0.01 | 0.3 | .614 | 0.00 | 0.3 | .581 | 0.00 |
| 5 | Rest × TOT | 2.130 | 4.3 | .015 | 0.06 | 1.2 | .319 | 0.02 | 1.2 | .310 | 0.02 |
| 6 | Demand × TOT | 2.130 | 81.0 | .000 | 0.56 | 23.5 | .000 | 0.27 | 0.5 | .637 | 0.00 |
| 7 | Rest × Demand × TOT | 2.130 | 2.1 | .122 | 0.03 | 0.4 | .681 | 0.00 | 1.6 | .204 | 0.02 |

*Note*: Effect size: partial $\eta^2$; experimental factors: rest breaks (continuous-work group vs rest-break group), demand (easy vs hard mental-arithmetic condition), time-on-task (TOT, bins 1–3).

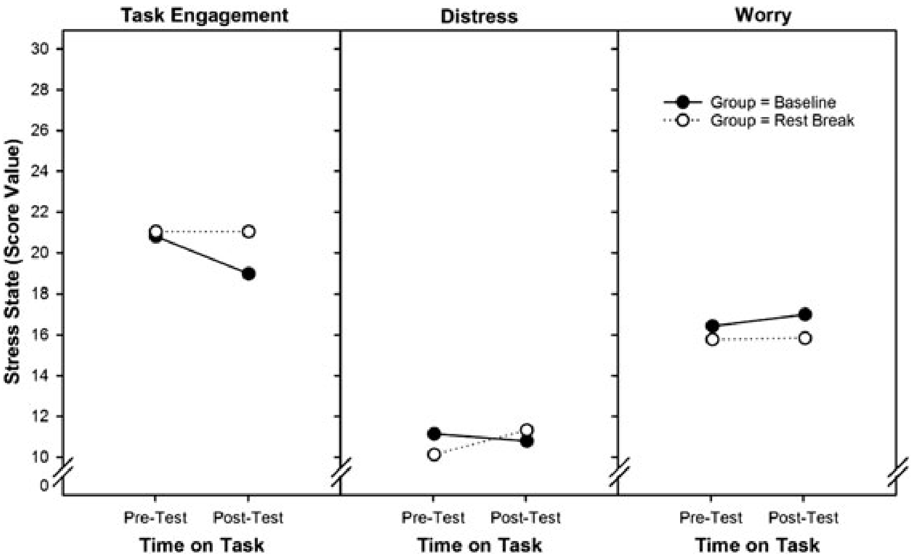

Figure 4. The three fundamental dimensions of subjective-stress state (task engagement, distress, and worry) as a function of the factors ‘rest’ (continuous-work group vs rest-break group), ‘demand’ (easy vs hard mental arithmetic), and TOT (before vs after the experimental session)

Table 3. Results of the experimental effects on subjective state (pre–post experimental comparison)

| Source | | | Task engagement | | | Distress | | | Worry | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *df* | | | *F* | *p* | $\eta^2$ | *F* | *p* | $\eta^2$ | *F* | *p* | $\eta^2$ |
| 1 | Rest (group) | 1.64 | 0.8 | .351 | 0.01 | 0.0 | .787 | 0.00 | 1.9 | .172 | 0.03 |
| 2 | TOT (pre–post) | 1.64 | 1.8 | .184 | 0.03 | 0.7 | .421 | 0.01 | 0.4 | .550 | 0.00 |
| 3 | Rest × TOT | 1.64 | 1.8 | .184 | 0.03 | 2.1 | .149 | 0.03 | 0.2 | .635 | 0.00 |

*Note*: Effect size: partial $\eta^2$; experimental factors: rest breaks (continuous-work group vs rest-break group), time-on-task (TOT: pre–post experimental comparison).

Table 4. Effects of rest, demand, and sequence (before rest vs after rest) on standard performance parameters

| Source | | | RTM | | | EP | | | RTCV | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *df* | | | *F* | *p* | $\eta^2$ | *F* | *p* | $\eta^2$ | *F* | *p* | $\eta^2$ |
| 1 | Rest (walk vs video) | 1.31 | 0.0 | .899 | 0.00 | 1.2 | .283 | 0.03 | 0.5 | .480 | 0.02 |
| 2 | Demand | 1.31 | 492.6 | .000 | 0.94 | 41.0 | .000 | 0.57 | 25.7 | .000 | 0.45 |
| 3 | Sequence | 1.31 | 46.9 | .000 | 0.60 | 0.5 | .486 | 0.02 | 0.0 | .892 | 0.00 |
| 4 | Rest × Demand | 1.31 | 0.1 | .730 | 0.00 | 7.7 | .009 | 0.20 | 0.6 | .426 | 0.02 |
| 5 | Rest × Sequence | 1.31 | 0.2 | .657 | 0.00 | 1.8 | .195 | 0.05 | 1.9 | .183 | 0.06 |
| 6 | Demand × Sequence | 1.31 | 35.1 | .000 | 0.53 | 1.1 | .298 | 0.04 | 0.7 | .414 | 0.02 |
| 7 | Rest × Demand × Sequence | 1.31 | 0.0 | .986 | 0.00 | 0.3 | .596 | 0.01 | 1.3 | .258 | 0.04 |

*Note*: Effect size: partial $\eta^2$; experimental factors: rest (walking vs watching a video), demand (easy vs hard mental arithmetic), sequence (before rest vs after rest).

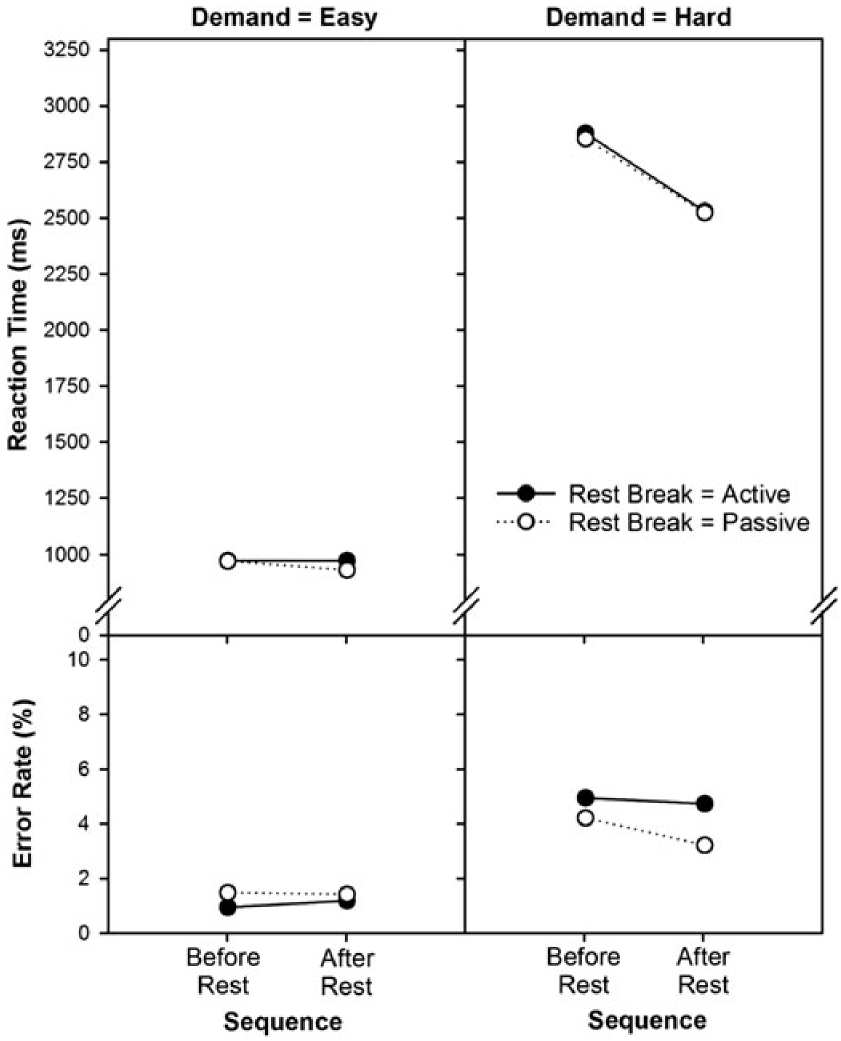

Figure 5. Reaction time mean and error percentage as a function of the within-subject factors ‘rest’ (active vs passive), ‘demand’ (easy vs hard), and ‘sequence’ (before vs after rest break) in continuous mental-arithmetic performance

## GLOBAL EFFECTS OF REST BREAKS ON PERFORMANCE

To examine the global effect of rest on performance, we compared RT performance between a continuous-work group and a rest-break group as a function of time at work, using a mental-arithmetic paradigm (Flehmig et al., 2010; Steinborn et al., 2008; Steinborn, Flehmig et al., 2010; Zbrodoff & Logan, 1990). We observed the beneficial effects of rest (vs continuous performance) in our study as this relative benefit increased with time at work. The responses became differentially faster across the session for the rest break (vs continuous-work), while error rate remained low overall. Thus, our study revealed that rest globally improves cognition. These findings are consistent with recent evidence in the domain of vigilance-detection tasks (Ariga & Lieras, 2011; Helton & Russell, 2015) but also extend these findings. In the self-paced situation, individuals have to actively attain and maintain an appropriate work speed, because each item follows immediately after the previous one (Steinborn & Langner, 2012; Vallesi, Lozano, & Correa, 2013). It is therefore even somewhat surprising that the individuals in our continuous-work group were quite capable to sustain performance over the task period with no considerable deterioration of performance.

According to Healy, Bourne, and colleagues (Healy et al., 2004; Healy et al., 2006), the result pattern observed in our study is expectable because both facilitation and inhibition occur during continuous mental arithmetic, with rest being capable to reduce inhibition. Facilitation results primarily from learning, while inhibition includes several processes, including fatigue, satiation, or a loss of engagement (Inzlicht & Schmeichel, 2012; Langner et al., 2011; Langner et al., 2010; Mojzisch & Schulz-Hardt, 2007). We were also able to show that the benefit of rest is more pronounced for hard (vs easy) arithmetic. Figure 1 shows that the relative benefit of rest increases differentially for the low-demand (vs high-demand) condition, amounting to 20 ms for the former but 200 ms for the latter condition. Thus, demand seems to be a critical variable that should not be ignored in future research. The finding that combined effects of rest and time at work are more pronounced under high (vs low) workload is consistent with a model proposed by Mojzisch and Schulz-Hardt (2007). Also, our results are consistent with findings reporting beneficial effects of rest on stimulus-detection performance in vigilance tasks, where response speed is less

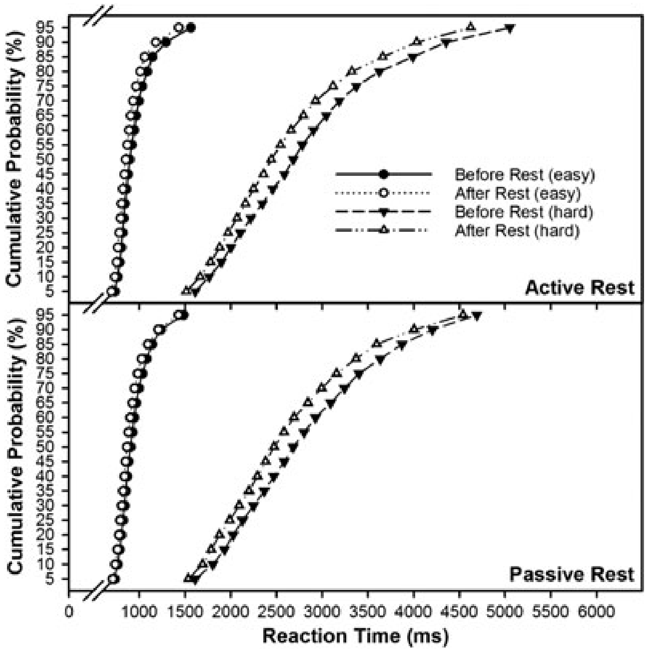

Figure 6. Vincentized cumulative distributive functions of reaction times for each combination of the within-subject factors 'rest' (active vs passive), 'demand' (easy vs hard), and 'sequence' (before vs after rest break) in continuous mental-arithmetic performance

important (Ariga & Lieras, 2011; Helton & Russell, 2015; Ralph, Onderwater, Thomson, & Smilek, 2016).

Some methodical rules should be considered in future studies: First, the response–stimulus interval is important, as it could be considered (among other functional mechanisms) a micro-break (plus preparatory) condition (Jentzsch & Dudschig, 2009; Rabbitt, 1969). The effects of rest breaks are predicted to be large when this interval is short but should decrease as this interval becomes longer. Historically, the performance decrement on mean RT with time at work has been explained by an increase in intraindividual response-speed variability originating from an accumulated refractory-phase effect, which can be reduced by increasing the intertrial interval (Dodge, 1917; Robinson & Bills, 1926; Weaver, 1942). Second, the length and frequency of rest breaks are important. Bills (1943, pp. 113–129) reviewed the body of empirical evidence in this domain, concluding that rest breaks should be brief (3–6 min) but frequent and should not exceed 8 min in length. Bills (1943, pp. 113–129) reasoned that any increase beyond the optimal length could result in a decrease in motoric arousal and might also increase the likelihood that individuals will lose the appropriate mindset to perform well (Van Breukelen et al., 1995).

## LOCAL EFFECTS OF REST BREAKS ON PERFORMANCE

To examine the local effect of rest on performance, we compared (within the rest-break group) the sequence of (100) trials immediately before and after a rest break. This analysis refers to a characteristic improvement of performance immediately after (vs before) rest (Adams, 1954; Bourne & Archer, 1956). The methodical approach is formally equivalent to an analysis of trial sequences surrounding a critical event, such as errors (Brewer & Smith, 1984; Steinborn, Flehmig, Bratzke, & Schroeter, 2012) or attentional lapses (Bertelson & Joffe, 1963; Steinborn et al., 2016). The responses were slow before rest but became faster afterward. Crucially, this effect was differentially larger for the high-demand mental-arithmetic condition as compared with the low-demand mental-arithmetic condition (Figure 5). Thus, our study revealed that rest locally (i.e., before vs after rest) improves performance in the context of a mental-arithmetic task. While the global rest-break effect might be a general phenomenon that can unequivocally be observed in both mental-work tasks (Healy et al., 2004; Healy et al., 2006) and vigilance-detection tasks (Ariga & Lieras, 2011; Helton & Russell, 2015), the local rest-break effect might be specific to the former as compared with the latter domain.

We hypothesized that active rest should be more effective than passive rest regarding its utility to restore cognitive resources during mental arithmetic. However, there was no difference between forms of rest, neither visually nor statistically (Table 4, Figures 5 and 6). This finding is particularly interesting, because it shows a divergence between what would intuitively be expected (Kahneman, 2013, p. 39) and what is actually observed in an experimental study. Very indirectly, studies on the effect of exercise on cognition would also deliver a clue as to the expectation that active forms of rest such as walking should be better than passive ones regarding both performance measures and subjective experience (Kanning & Schlicht, 2010; Sanabria et al., 2011; Thayer, Newman, & McClain, 1994; Tomporowski, 2003). Thus, we feel obliged at this point to explain the lack of any difference — or put it another way — the perfect similarity between both conditions in our study. We argue that the critical elements in the study of active versus passive rest depend on three key variables that might be addressed in future research: the task paradigm, the environmental conditions, and walking (exercise) intensity (Brisswalter, Collardeau, & Arcelin, 2002).

In mental-work tasks, individuals have to actively engage in cognitive activity, which means that task sets must be attained and maintained throughout the session. This is accompanied by a rather global activation and greater scope for compensatory effects of momentarily decreased mental efficiency. In vigilance-detection tasks, on the other hand, individuals engage in a more passive watch-keeping activity. There is no doubt that attentional monitoring involves kinds of mental activity that are experienced as effortful and tap on cognitive resources (Warm, Parasuraman, & Matthews, 2008), but the extent and type of demand being placed upon individuals are particularly different, with respect to both proactive (e.g., the opportunity to actively engage) and reactive (e.g., response-induced motoric arousal) mechanisms. As reported by Bratzke et al. and Steinborn et al. (Bratzke, Rolke, Steinborn, & Ulrich, 2009; Bratzke, Steinborn, Rolke, & Ulrich, 2012; Steinborn, Bratzke, et al., 2010), the deterioration of performance as a result of energetic variables (sleep loss and circadian rhythms) is less severe for speeded-decision tasks than for vigilance-detection tasks. Presumably, there is more room to compensate for momentary states of low arousal by a mobilization of effort in speeded tasks than to increase attention in vigilance-detection tasks (Sanders, 1998, pp. 394–430).

## EFFECT OF REST BREAKS ON PERFORMANCE SPEED VERSUS VARIABILITY

Probability distributions have often been analyzed to gain information beyond that obtainable from the RT mean alone (Miller, 2006; Reynolds & Miller, 2009). The incremental information available from the analysis of empirical RT distributions provides important clues as to the precise causes of differences in experimental conditions in the RT mean (Heathcote et al., 1991; Leth-Steensen, Elbaz, & Douglas, 2000; Steinhauser & Huebner, 2009). The present study contributes to this trend of analyzing RT distributions by addressing the question of whether the effect of rest breaks on the mean RT performance is uniformly observed across all percentiles of the CDF, or alternatively, whether the effect is selective with respect to the slowest percentiles of the CDF, respectively (Steinborn et al., 2016). Is the effect of rest present in every trial or does it instead arise only in occasional trials, perhaps as a result of an occasional failure to maintain attentional focus? In general, our results indicate that rest breaks are not that selective (with respect to only the slowest CDF percentiles) as one might expect from previous findings and theoretical considerations (refer to Figures 2, 3, and 6). One might conclude, therefore, that rest primarily improved processing speed in our study.

We asked whether the effect of rest originates from a selective shift of slower CDF percentiles or from a parallel effect of all CDF percentiles. The former is indicated by the proportion of time units, during which operations are carried out effectively (vs ineffectively, as a result of lapsing), while the latter refers to mere speed-up in the computation of processes. Our understanding of attentional restoration by rest might depend (at least partly) on whether rest affects all percentiles uniformly (speed) or selectively (variability). While the factor demand separately had a strong effect on RT variability (more demand increases distributional skewness), the factor rest improves performance fairly equally. Very tentatively, one could infer from the visual patterning that the global rest-break effect is somewhat more pronounced in the slower than in the faster percentiles. Figure 3 displays a delta plot of the TOT effect, separately for the continuous-work condition and the rest-break condition. A delta plot is obtained by calculating the RT difference as induced by an experimental manipulation against the mean of the experimental conditions for each of the percentiles. By this means, the effect of the critical factor can be evaluated relative to the mean performance level.

The delta-plot analysis indicates a relative benefit of the rest-break condition over the continuous-work condition with respect to the slower CDF percentiles. This analysis might deliver a clue as to the possibility that the individuals in the rest-break condition did not only become faster overall but especially became more persistent. In the overall picture, however, we conclude that rest improves self-paced RT performance rather uniformly. The data indicate that rest primarily improves processing speed — a result that stands somewhat in contrast to previous research. In fact, it has been theorized that the probability of committing attentional failure (mental blocks) is reduced through rest. For example, Bertelson and Joffe (1963) used self-paced four-choice task with four stimuli mapped onto four corresponding keys. Sanders and Hoogenboom (1970) used a six-choice RT task with six stimuli mapped onto six keys. This arrangement is much simpler and more repetitive than the one used in our study, providing fewer possibilities for procedural learning. The difference between these and our results might therefore be a result of the differences in the potential for procedural learning (Lim, Teng, Wong, & Chee, 2016; Steinborn, Bratzke, et al., 2010).

## CONCLUSION AND FUTURE DIRECTIONS

The general message of our study is that rest improved performance, as this effect increased with time at work, being more pronounced for high-demand mental arithmetic than for low-demand mental arithmetic. Our study might provide a useful extension to previous research in the domain of vigilance-detection tasks (Ariga & Lieras, 2011; Helton & Russell, 2015) as well as practical implications for the utility of rest breaks at work, during psychometric testing (Hagemeister, 2007; Krumm, Schmidt-Atzert, & Eschert, 2008) and in everyday life (cf. Flehmig, Steinborn, Langner, & Westhoff, 2007). Future research might orient their focus on specific mechanisms supported by brief rest or other energetical variables such as background stimulation (Hommel, Fischer, Colzato, van den Wildenberg, & Cellini, 2012; Szalma & Hancock, 2011), supervision (Brewer, 1995; Brewer & Ridgway, 1998; Wühr & Huestegge, 2010), or evaluative pressure (Gray, 2011). Further, it remains to be clarified of whether rest enhances performance effectiveness through a restored ability to focus on the relevant information-processing features, or alternatively, through a temporal stabilization of continuous information processing. It might also be explored whether rest supports the use of effective mental representations which support effective strategies. In the light of the pronounced effect of rest on performance in difficult tasks, this issue could be especially interesting in the context of multitasking demands (Huestegge, Pieczykolan, & Koch, 2014) or visual search in complex environments (Huestegge & Radach, 2012).

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