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Boosting arousal and cognitive performance through alternating posture: Insights from a multi-method laboratory study

Henk van Steenbergen[1,2] | Tom F. Wilderjans[2,3,4] | Guido P. H. Band[1,2] | Sander T. Nieuwenhuis[1,2]

[1]Cognitive Psychology Unit, Institute of Psychology, Leiden University, Leiden, The Netherlands

[2]Leiden Institute for Brain and Cognition, Leiden, The Netherlands

[3]Methodology and Statistics Unit, Institute of Psychology, Faculty of Social and Behavioral Sciences, Leiden University, Leiden, The Netherlands

[4]Research Group of Quantitative Psychology and Individual Differences, Faculty of Psychology and Educational Sciences, KU Leuven, Leuven, Belgium

Correspondence
Henk van Steenbergen, Cognitive Psychology Unit, Institute of Psychology, Leiden University, Wassenaarseweg 52, AK Leiden 2333, The Netherlands.
Email: hvansteenbergen@fsw.leidenuniv.nl

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Abstract

This study investigated the role of arousal and effort costs in the cognitive benefits of alternating between sitting and standing postures using a sit-stand desk, while measuring executive functions, self-reports, physiology, and neural activity in a 2-h laboratory session aimed to induce mental fatigue. Two sessions were conducted with a one-week gap, during which participants alternated between sitting and standing postures each 20-min block in one session and remained seated in the other. In each block, inhibition, switching, and updating were assessed. We examined effects of time-on-task, acute (local) effects of standing versus sitting posture, and cumulative (global) effects of a standing posture that generalize to the subsequent block in which participants sit. Results ($N=43$) confirmed that time-on-task increased mental fatigue and decreased arousal. Standing (versus sitting) led to acute increases in arousal levels, including self-reports, alpha oscillations, and cardiac responses. Standing also decreased physiological and perceived effort costs. Standing enhanced processing speed in the flanker task, attributable to shortened nondecision time and speeded evidence accumulation processes. No significant effects were observed on higher-level executive functions. Alternating postures also increased heart rate variability cumulatively over time. Exploratory mediation analyses indicated that the positive impact of acute posture on enhanced drift rate was mediated by self-reported arousal, whereas decreased nondecision time was mediated by reductions in alpha power. In conclusion, alternating between sitting and standing postures can enhance arousal, decrease effort costs, and improve specific cognitive and physiological outcomes.

KEYWORDS

arousal, body posture, executive function, mental fatigue, sit-stand desk

1 | INTRODUCTION

Humans are not physiologically suited to spend most of their time sitting, thinking, and typing (Bonnet & Cheval, 2023). However, in modern office jobs, people perform intense mental work in environments that encourage little physical activity. Occupational sitting is likely the biggest contributor to overall daily sitting time, which is a significant risk factor for obesity, diabetes, cardiovascular disease, and mortality, even irrespective of physical activity during leisure (Sui et al., 2019; Thorp et al., 2011; van Uffelen et al., 2010). Therefore, it is important to develop innovations that help reduce sitting time to mitigate these poor health outcomes (Bonnet & Cheval, 2023). One promising recent development in this regard is the introduction of height-adjustable sit-stand desks in offices worldwide. These desks enable office workers to alternate between sitting and standing postures while doing office work (MacEwen et al., 2015; Sui et al., 2019; van der Ploeg et al., 2014). By enabling office workers to break up prolonged sitting with standing and movement, sit-stand desks offer a simple and promising way to mitigate the health risks associated with sedentary behavior.

While there is evidence that regularly breaking up sitting sessions can reduce sedentary behavior and benefit physical health (Chastin et al., 2015), whether and how alternating between sitting and standing postures impacts cognitive function remains unclear. One reason for this knowledge gap, is that most studies so far have focused on acute effects. These studies provided mixed findings. Some lab studies have suggested that standing posture improves attentional focus and working memory (Bhat et al., 2022; Dodwell et al., 2019; Rosenbaum et al., 2017; Smith et al., 2019), while others have failed to replicate these effects (Caron et al., 2020; Ohlinger et al., 2011; Straub et al., 2022). Other studies in work settings have suggested that most performance measures remain unaffected by a standing posture (Commissaris et al., 2014; Husemann et al., 2009; Russell et al., 2016; Sui et al., 2019), or that benefits are limited to performance speed (Vercruyssen & Simonton, 2020).

In order to reveal effects that extend beyond the acute effects of bouts of standing, it is imperative to use an experimental design where cognitive performance is also measured following this bout, preferably in an alternating sitting-standing schedule that mirrors real work environments. To the best of our knowledge, only one study has combined such a schedule with repeated cognitive measures. This study showed that short bouts of standing accumulate into improved cognitive performance when considering averaged performance over an entire working day (Mullane et al., 2017). However, their analysis lacked the temporal resolution necessary to shed light on the exact timing and progression of posture-induced cognitive changes. Hence, further investigation is warranted to unravel the specific cognitive alterations that occur immediately and over time as individuals alternate between sitting and standing.

The primary aim of the present study was to bridge this gap by investigating how alternating between a standing and sitting posture every 20 min over the course of 2 h of intensive mental work affects performance on three computer tasks assessing key components of executive function, namely inhibition, switching, and updating (Miyake et al., 2000). As illustrated in Figure 1a, we compared these effects to a prolonged sitting condition in which the same participants, in a different session, performed the tasks without adopting changes in posture. Assuming that performance declines with time-on-task due to mental fatigue in the prolonged sitting condition and that standing is beneficial, we can anticipate two possible scenarios. Firstly, as depicted in Figure 1b, if standing only provides temporary improvements that do not carry over to later periods, we might observe short-term effects during the standing intervals. These effects would simply add to the impact of time in the prolonged sitting condition. We refer to these effects as local effects of posture, forming a zigzag pattern. Secondly, as illustrated in Figure 1c, if the benefits of standing not only manifest acutely but also extend beyond the immediate timeframe, we should witness a carry-over of this improvement to the subsequent sitting block. This would counteract the time-related decline observed during prolonged sitting. We refer to this change in the "time slope" across sitting blocks as global effects of posture.

The second aim of our study was to understand the mechanism that underlies the potential cognitive benefits of standing. Our study therefore used a multi-method, comprehensive approach and assessed arousal, mental fatigue, and effort costs across various domains covering the subjective, physiological, and neural level. Earlier work has shown that prolonged sitting increases mental fatigue and the perceived effort costs of mental work, while it reduces arousal and hampers motivation and executive functions, both in lab studies as well as in applied settings (Baker et al., 2018; Blain et al., 2016; Boksem et al., 2005; Boksem & Tops, 2008; Hopstaken et al., 2015a, 2015b; Lorist et al., 2005; Thorp et al., 2011). Consistent with a beneficial effect of posture-induced arousal hypothesized earlier (Caldwell et al., 2003; Lambourne & Tomporowski, 2010), a few studies have started to show that a standing body posture can counteract the accumulated mental fatigue and effort costs associated with prolonged sitting, and prevents declines in physiological and subjective arousal levels over time (Ebara et al., 2008; Hasegawa et al., 2001). Indeed, it is well known that changing from a sitting to a standing posture sets in motion a complex cascade of physiological

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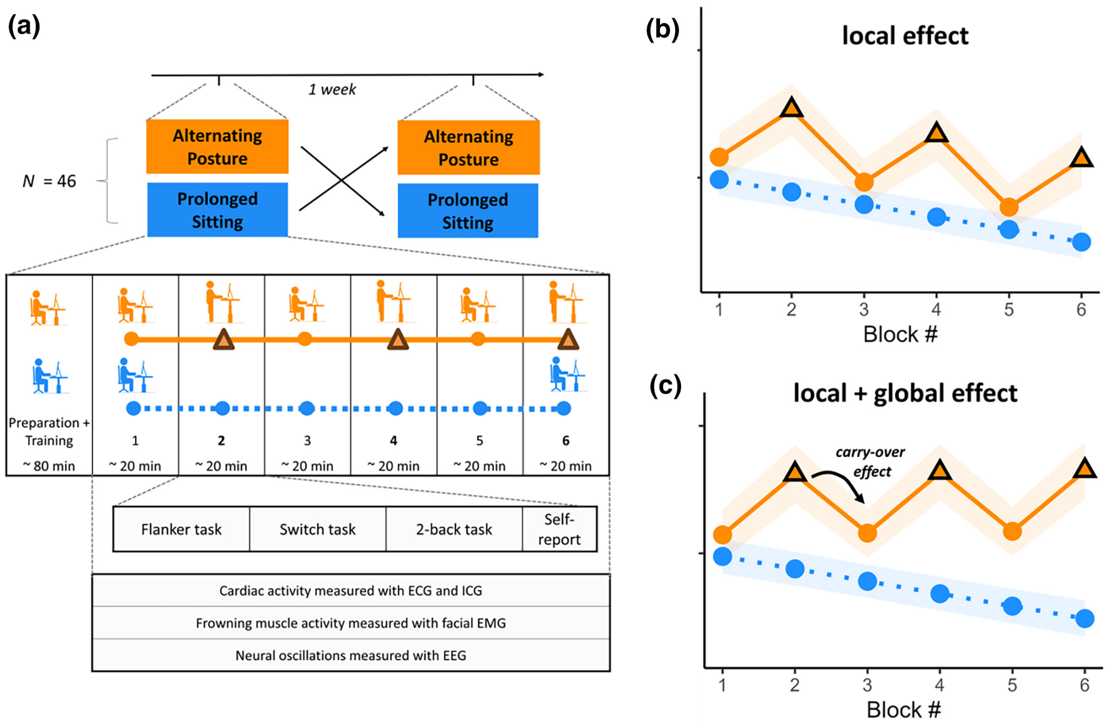

FIGURE 1 (a) Study design. Participants performed the same set of executive function tasks under two conditions, tested in two sessions separated by a week (counterbalanced order). After preparation and practice of the tasks, participants performed all three tasks (in counterbalanced order) during a 2-h testing period. During the Alternating Posture condition participants alternated between a sitting or standing posture in each block; during the Prolonged Sitting condition they remained seated in all six blocks. Note that posture only differed in the even-numbered blocks (2, 4, and 6). (b, c) Illustration of local and global effects of posture across the 2-h testing period spanning six blocks. Sitting-posture blocks are represented by circles, while standing-posture blocks are represented by triangles.

changes to compensate for blood volume displacement, resulting in increased sympathetic activity as visible in heart-rate increases and increased low-frequency contributions to heart rate variability (Ebara et al., 2008; Houtveen et al., 2005; Smith et al., 1994). This sympathetic activity, in turn, activates the locus-coeruleus system and the release of norepinephrine in the brain (Berridge & Waterhouse, 2003; Robertson et al., 1979; Tulen et al., 1999), which has been implied in cognitive changes via modulations of neural gain (Aston-Jones & Cohen, 2005; Ferguson & Cardin, 2020; Lambourne & Tomporowski, 2010; Thibault et al., 2014). These modulations in neural arousal might also be visible in scalp recordings of neural brain oscillations measurable with electroencephalography (EEG). Indeed, some EEG studies have observed effects of posture and mental fatigue in the lower-frequency bands, although these findings are not consistent (Boksem et al., 2005; Caldwell et al., 2003; Labonté-LeMoyne et al., 2020; Thibault et al., 2014). Sympathetic arousal increases might also reduce effort costs associated with mental fatigue (Hockey, 1997; Massar et al., 2019; Mlynski et al., 2021), and we therefore included perceived effort ratings as well as facial electromyography (fEMG) over the corrugator supercilii (frowning) muscle as a physiological index of effort costs (Berger et al., 2020).

Our confirmatory two-step mediation analyses tested the hypothesis that standing induces sympathetic arousal (heart rate increase), which results in neural arousal that, in turn, improves cognitive performance. To explore the potential relationship between posture-induced changes in arousal and effort costs measured at different levels, we conducted correlational analyses, recognizing that they may represent distinct aspects of multidimensional constructs (Neiss, 1988; Thomson & Oppenheimer, 2022). Finally, we ran exploratory mediation analyses to determine which measures mediated the posture-induced benefits on performance.

2 | METHODS

2.1 | Participants

In total, 69 volunteers participated in this experiment. Inclusion criteria were: age between 18 and 30 years, having a higher professional or university education level, fluent in Dutch, no dreadlocks or braids, no use of medication (excluding contraceptives and allergy medication), no physical limitations that make sitting or standing painful or impossible, and no history of psychiatric illnesses or head injury (excluding minor concussion). Participants were asked to not eat, drink, and sleep differently than usual, but to have a meal before the sessions started. Data was collected between October 2015 and March 2016. We stopped collecting data after we obtained complete datasets for all modalities for at least 40 participants.

Due to space limitations, details about subject exclusion are described in the supplement. A full overview of all included data is available in Table S1.

A sensitivity analysis revealed that with the remaining sample of 46 participants we were able to detect within-subject effects with two-tailed t-tests of $d = 0.422$ with 80% power. This effect size approximates the average effect size observed in the field of social psychology, which is $r = .21$ (equivalent to $d = 0.43$) (Richard et al., 2003), and the effect size of $d = 0.4$ that has been described as typical for psychological research (Brysbaert & Stevens, 2018). Note that although we did not run formal simulations to determine the power analyses, the mixed models we applied might actually be more powerful than paired t-tests because they have been argued to provide a better estimate of the random effect structure (Bell et al., 2019). On the other hand, the between-subject correlation-based analyses reported, including the mediation analyses, were underpowered to detect these relatively small effect sizes, because with 46 participants and 80% power the r would need to be .399. Event-related analyses of the cardiac response to errors during the Prolonged Sitting condition have been published separately elsewhere (Spruit et al., 2018).

2.2 | Design

As shown in Figure 1, over the course of 2 h, participants repeatedly performed three computer tasks assessing the three key components of executive function, namely inhibition, switching, and updating (Miyake et al., 2000). This relatively long period was chosen to induce arousal reductions and mental fatigue, which are typically observed in lab studies that combine time-on-task manipulations with prolonged sitting (Boksem et al., 2005; Boksem & Tops, 2008; Hopstaken et al., 2015a, 2015b; Lorist et al., 2005). Testing was preceded by substantial pre-training to eliminate potential learning effects. All participants practiced the tasks while seated, and this took about 20 to 45 min. Behavioral, physiological, and neural changes were measured in six blocks lasting about 20 min each. Participants came to the lab in two sessions separated by a week: in one session, participants alternated between sitting and standing (Alternating Posture condition), whereas in the other session, participants remained seated during the entire session (Prolonged Sitting condition). The order was counterbalanced. The Prolonged Sitting condition served as our control condition and was expected to induce mental fatigue and cognitive decline over time, while the Alternating Posture condition was expected to counteract these effects.

Mimicking office work settings, participants' arms were supported by the desk. This also avoided extra physiological and motor demands involved in maintaining balance, which have been shown to negatively impact cognition (Bayot et al., 2018; Fraizer & Mitra, 2008). The participants performed three tasks to assess inhibition, switching, and updating: a modified version of the flanker task (Eriksen & Eriksen, 1974; Lorist et al., 2005), a switch task (Rondeel et al., 2015), and a 2-back working memory task (Hopstaken et al., 2015a). The tasks took about 6 min each and were performed in each of the six blocks. The order of the tasks in each block stayed constant for each participant but was counterbalanced across participants.

During the practice block, the participant received visual feedback (average reaction time (RT) and accuracy) and auditory feedback (male voice) after responding to a target ("correct button", "incorrect button" or "no button"). The experimenter repeatedly presented a practice block for each task until participants reached a certain criterion. For the 2-back working memory task, ≥85% correct responses were required. The flanker task required ≥85% correct responses and a mean RT ≤ 500 ms. The switch task required ≥85% correct responses and a mean RT ≤ 1200 ms. However, due to time constraints, when practice took longer than approximately 45 min, participants started the task proper even if they did not meet all criteria.

2.3 | Materials

E-Prime 2.0 was used to present the tasks. The flanker task and switch task were described in detail elsewhere (Spruit et al., 2018). The two-back working memory task was modeled after an earlier study (Hopstaken et al., 2015a) and consisted of 63 trials on which one of the letters B, C, D, E, G, J, P, T, or V was presented for 500 ms. These letters all have similar sounds in Dutch, so it is impossible to use sound-related memory strategies. The letters were presented in a font size of 40 points type Palatino Linotype. The participants were to remember earlier presented letters and indicate if the one currently presented matched the one seen two trials earlier. The maximum RT allowed was 4000 ms. Each block consisted of 15 targets and 48 nontargets presented at a fixation point for a random duration between 5000 and 5500 ms. The total time of each task was 6 min.

2.4 | Procedure

Participants were tested in two sessions that lasted approximately 3.5 to 4 h each. The experiment took place in an EEG lab booth of approximately 2 × 2 m. Participants started in a seated position in a conference chair at an electrical, height-adjustable sit-stand desk on which the computer screen (approximately 50 cm from the participant), keyboard, and mouse were placed. Participants were informed about the procedure of the experiment, provided informed consent, and read the instructions of the affect grid (Russell et al., 1989). This study was approved by the local ethics committee. It was not preregistered.

After application of the ECG and ICG electrode patches, participants started the practice block. To minimize potential learning effects, in each session, the three cognitive tasks were practiced until the criteria mentioned above were met. After the practice, the EEG, fEMG, and EOG electrodes were applied. Participants were instructed not to talk and to minimize movements while performing the task. Each of the six test blocks took about 18 min in which all three tasks were performed. After each test block, four visual analog scales (VAS) and the 9 × 9 affect grid were presented on the screen. The affect grid was also presented before the first block, but these values were not included in the analyses in order to keep the analysis the same for all dependent variables. The VAS ranged from 0 (not at all) to 100 (extremely) and included the following items (see also Hopstaken et al., 2015a): (1) You just performed a task for 20 min. How tired do you feel now? (2) How motivated did you feel to perform well during the last block? (3) How much effort did you spend to perform well during the last block? (4) How much aversion do you feel to start the next block?

In between blocks, the researcher could enter the lab booth to adjust the table or to optimize the physiological recordings. In the first session, the researcher was blinded to the condition the participant was in until the first block had ended. After the third block, the researcher offered each participant a glass of water. In total, it took about 2 h to complete the six blocks. At the end of the second session, participants were given a written debriefing and either received course credits or participated in a lottery to receive monetary compensation.

2.5 | Data acquisition

The EEG and facial electromyography (fEMG) data were acquired using BioSemi equipment. Signals were DC amplified and digitized at a sampling rate of 1024 Hz using the ActiView705-Lores application. Brain activity was measured at the midline locations Fz, FCz, Cz, CPz, and Pz. The common mode sensor and driven right leg were used as standard reference. To allow for correction of ocular artifacts in the EEG data, we also obtained electrooculography (EOG) measures. To measure horizontal eye movement, two electrodes were placed on the orbicularis muscle on the edge of the eye socket. To measure vertical eye movement, electrodes were placed just above the left eyebrow and below the left eye on the edge of the eye socket. In order to re-reference the data offline, we placed two electrodes on the mastoids behind the ears. Finally, to measure facial EMG, two electrodes were placed on the corrugator muscle of the right eye.

Electrocardiography (ECG) and impedance cardiography (ICG) signals were continuously measured using a Biopac system. Details are described elsewhere (Spruit et al., 2018).

2.6 | Data preprocessing

In order to obtain the dependent variables that were submitted to the statistical analyses (see Table 1 for an overview of all dependent variables), we applied preprocessing for each modality, as specified below.

2.6.1 | EEG preprocessing

For the analysis of the total power, artifact-free segments of EEG data with a length of 2 seconds were extracted from the continuous ongoing EEG during the six task blocks. The resulting segments were submitted to a fast Fourier transform (FFT) to get power spectra with a spectral resolution of 0.25 Hz, which was then averaged across segments. The power in the FFT was extracted for delta activity (1–4 Hz), theta activity (4–8 Hz), alpha activity (8–12 Hz), and beta activity (12–30 Hz). In the statistical analyses, we used the log-transformed data to correct for the skew in the data we observed during initial data screening.

2.6.2 | fEMG preprocessing

Facial EMG activity was analyzed using Brain Vision Analyzer software. EMG data were high-pass filtered at 20 Hz and low-pass filtered at 500 Hz. Line noise was removed using a 50-Hz notch filter. We calculated the root mean square (RMS) of the facial EMG data for all 2-s artifact-free segments, averaged for each 1-min (six in total) per block per task. Artifacts were detected for

TABLE 1 Overview of the main findings for all dependent variables.

Cluster and dependent variable	Effect of time: Mean [95% CI]	p	p (fdr)	Local effect of posture: Mean [95% CI]	p	p (fdr)	Global effect of posture: Mean [95% CI]	p	p (fdr)
Self-report									
Self-reported arousal (1–9)	**−1.457 [−1.958, −0.956]**	**<.001**	**<.001**	**0.508 [0.245, 0.772]**	**<.001**	**<.001**	0.618 [0.017, 1.219]	.049	.147
Self-reported aversion next block (0–100)	**12.845 [6.878, 18.811]**	**<.001**	**<.001**	−3.357 [−6.871, 0.157]	.063	.094	6.188 [−0.843, 13.219]	.090	.180
Self-reported effort required (0–100)	*7.870 [0.328, 15.413]*	*.046*	*.054*	**−4.311 [−7.823, −0.799]**	**.020**	**.040**	*0.270 [−8.179, 8.719]*	*.950*	*.957*
Self-reported engagement (0–100)	***−24.644 [−31.823, −17.464]***	***<.001***	***<.001***	0.221 [−2.806, 3.247]	.886	.886	*7.446 [1.059, 13.833]*	*.027*	*.147*
Self-reported pleasure (1–9)	−0.525 [−1.045, −0.006]	.054	.054	0.253 [−0.024, 0.531]	.079	.095	−0.309 [−0.947, 0.330]	.347	.520
Self-reported tiredness (0–100)	***15.206 [8.265, 22.148]***	***<.001***	***<.001***	**−5.620 [−9.043, −2.197]**	**.002**	**.006**	0.185 [−6.538, 6.907]	.957	.957
Facial electromyography									
Corrugator muscle activity (mV)	**−0.166 [−0.316, −0.016]**	**.034**	**.034**	**−0.347 [−0.455, −0.238]**	**<.001**	**<.001**	0.019 [−0.128, 0.165]	.805	.805
Cardiac									
Heart Rate (bpm)	**−4.858 [−5.974, −3.741]**	**<.001**	**<.001**	**10.761 [9.480, 12.043]**	**<.001**	**<.001**	**−1.677 [−3.147, −0.207]**	**.031**	**.031**
RZ-interval (ms)	−0.206 [−2.692, 2.280]	.872	.872	**5.096 [3.644, 6.547]**	**<.001**	**<.001**	***6.247 [3.085, 9.408]***	***<.001***	***<.001***
Heart Rate Variability	**10.081 [6.214, 13.948]**	**<.001**	**<.001**	**−30.078 [−36.892, −23.264]**	**<.001**	**<.001**	**13.180 [7.478, 18.883]**	**<.001**	**<.001**
Neural oscillations									
Global EEG delta power (ln)	**0.107 [0.024, 0.190]**	**.014**	**.028**	−0.007 [−0.058, 0.044]	.790	.790	0.102 [0.014, 0.190]	.028	.112
Global EEG theta power (ln)	0.043 [−0.013, 0.099]	.130	.130	−0.043 [−0.087, −0.000]	.050	.089	0.057 [−0.008, 0.122]	.085	.170
Global EEG alpha power (ln)	**0.174 [0.090, 0.258]**	**<.001**	**<.001**	**−0.098 [−0.155, −0.041]**	**.001**	**.004**	0.006 [−0.077, 0.088]	.891	.891
Global EEG beta power (ln)	0.048 [−0.014, 0.111]	.130	.130	−0.044 [−0.090, 0.003]	.067	.089	0.018 [−0.058, 0.094]	.637	.849
Behavior									
Working memory performance	*−0.265 [−0.524, −0.006]*	*.051*	*.051*	0.081 [−0.089, 0.251]	.349	.349	0.171 [−0.176, 0.518]	.339	.339
Flanker—Congruency effect RT (ms)	−2.786 [−9.174, 3.601]	.394	.525	−1.234 [−7.255, 4.786]	.688	.886	−6.212 [−15.044, 2.620]	.171	.684
Flanker—Congruency effect Error Rate	0.002 [−0.013, 0.018]	.767	.859	−0.004 [−0.018, 0.010]	.582	.886	−0.007 [−0.028, 0.014]	.530	.712
Flanker—Overall RT (ms)	**23.085 [11.629, 34.542]**	**<.001**	**<.001**	**−21.930 [−29.834, −14.026]**	**<.001**	**<.001**	−0.629 [−13.979, 12.722]	.927	.981
Flanker—Overall Error Rate	0.009 [−0.002, 0.021]	.113	.301	−0.001 [−0.010, 0.008]	.799	.886	*−0.000 [−0.012, 0.011]*	*.981*	*.981*
Switch—Switch costs RT (ms)	*−2.185 [−26.265, 21.896]*	*.859*	*.859*	−7.998 [−26.632, 10.635]	.402	.886	11.511 [−24.625, 47.647]	.534	.712
Switch—Switch costs Error Rate	0.012 [−0.013, 0.038]	.349	.525	0.001 [−0.018, 0.020]	.886	.886	−0.015 [−0.049, 0.019]	.384	.712

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TABLE 1 (Continued)

Cluster and dependent variable	Effect of time Mean [95% CI]	*p*	*p* (fdr)	Local effect of posture Mean [95% CI]	*p*	*p* (fdr)	Global effect of posture Mean [95% CI]	*p*	*p* (fdr)
Switch—Overall RT (ms)	31.436 [−5.293, 68.165]	.101	.301	−16.134 [−36.327, 4.058]	.119	.476	28.269 [−7.606, 64.144]	.129	.684
Switch—Overall Error Rate	0.006 [−0.002, 0.014]	.157	.314	−0.001 [−0.009, 0.007]	.813	.886	−0.005 [−0.016, 0.007]	.402	.712
Computational modeling									
Flanker—drift rate (v)	**−0.065 [−0.089, −0.042]**	**<.001**	**<.001**	**0.023 [0.007, 0.038]**	**.005**	**.007**	−0.000 [−0.025, 0.024]	.969	.969
Flanker—nondecision time (Ter)	0.002 [−0.006, 0.010]	.660	.660	**−0.012 [−0.020, −0.005]**	**.001**	**.003**	−0.006 [−0.018, 0.006]	.361	.969
Flanker—boundary separation (a)	0.003 [−0.001, 0.007]	.104	.156	−0.003 [−0.006, 0.001]	.150	.150	0.000 [−0.004, 0.005]	.856	.969

Note: Effects with $p < .05$ are in black, otherwise in gray. Values that survive FDR-correction are in bold. When a significant time, local, or global effect is significantly moderated this is indicated in italics. More details are available in Table S2.

each 100-ms bin using an algorithm described in detail elsewhere (Dignath et al., 2019). The average RMS value was then exported. In the statistical analyses, we applied square-root transformation to these values to correct for the skew in the data we observed during initial data screening.

2.6.3 | Cardiac data preprocessing

Preprocessing was performed in MATLAB release 2012b (The MathWorks, Inc., Natick, MA, USA) using the PhysioData toolbox (v0.1.8l; https://physiodatatoolbox.leidenuniv.nl/). Details are described elsewhere (Spruit et al., 2018). Heart rate variability was calculated using the root mean square of successive differences. We exported all cardiac metrics separately for each block and task for statistical analyses.

2.6.4 | Behavioral preprocessing

For the working memory task that prioritized accuracy, we extracted measures of sensitivity (d-prime) based on signal detection theory (Stanislaw & Todorov, 1999). In the two speeded tasks (flanker task and switch task) we extracted correct RT and error rate, separately for each session, block, task, and task condition (congruent/incongruent, switch/repeat). The first trial of each block and trials following an error were excluded. For the RT analyses, we removed RTs that exceeded two standard deviations around the mean, separately for each subject and cell of the design. We then calculated mean overall measures of RT and ER, as well as the corresponding congruency effects and switch costs, which were exported for statistical analyses.

2.6.5 | Estimating drift diffusion modeling parameters based on behavioral data

We implemented the EZ-drift diffusion model (Wagenmakers et al., 2007) to extract latent parameters of drift rate, boundary separation and nondecision time. This model fitted parameters based on average correct RT, the variance in correct RT, and the proportion of correct responses of the flanker task. We applied standard edge correction for proportion correct values of 1 (minus half of an error/n), .5 (minus half of an error/n), and 0 (plus half of an error/n). Model fitting was done separately for each subject, session, block, and level of congruency. The data was then averaged across the two congruency levels and exported for statistical analyses.

2.7 | Statistical analyses

We first automatically detected potential outliers for each cell of the design using the identify_outliers function in the rstatix package version 0.7.2 (Kassambara, 2021). Values above Q3 + 1.5 × IQR or below Q1—1.5 × IQR were considered as outliers and replaced by missing values.

Because the order of sitting and standing blocks in the Alternating Posture condition was fixed (alternating order: i.e., sit–stand–sit–stand–sit–stand) rather than randomly determined, the global and local effects of posture were potentially confounded. We therefore used a regression approach to statistically control for these time-related effects. We applied linear mixed-effect models which allowed us to maximally use all available data, even if some observations (on the dependent variable under study) were missing. The same analysis pipeline in R (version 4.3.0) was applied to all dependent variables in a fully automatic way.

We applied a linear mixed model to the data where outliers were replaced by missing values. To specify, we built a model that took into account the linear effect of Time across the six blocks (T: values ranged from −.5 to .5 in 6 equal steps), the effect of Condition (C: Prolonged Sitting condition = 0; Alternating Posture condition = 1), and the effect of even-numbered versus odd-numbered blocks (E: even = 1; odd = 0), all as within-subject predictors. We also added the between-subject factor Order (O) as numeric confound regressor (prolonged sitting during session 1/alternating posture during session 2 = −1; alternating posture during session 1/prolonged sitting during session 2 = 1).

Note that we carefully chose and coded the levels of the predictors so that the effects of interest were estimated at the correct reference level (value 0) of all other predictors. To test the main hypotheses, our analysis focused on three effects: (1) a local effect of standing versus sitting posture in the Alternating Posture condition, over and above time-related effects of even- versus odd-numbered blocks in the Prolonged Sitting condition, as evidenced by the interaction effect of C × E; (2) an effect of time-on-task in the Prolonged Sitting condition, as evidenced by a significant linear effect (slope) of T, estimated at the reference level of prolonged sitting ($C = 0$) and odd blocks ($E = 0$); (3) a global effect of alternating body posture versus continuously sitting, revealed by a modulation of time-on-task-related effects (i.e., modulation of the slope) considering sitting blocks only, as evidenced by a significant interaction effect $T \times C$ (estimated during the odd-numbered blocks, $E = 0$). Analyses of simulated data reported in the Supplementary Material and Figure S1 confirmed that our model could successfully capture these effects under different scenarios.

For all analyses, we a priori kept at least the following terms in the model: the effects of T, C, E, and O, as well as the two-way interaction effects of T × C (reflecting the global effect of posture), C × E (reflecting the local effect of posture), T × O (reflecting the time slope during the prolonged sitting session moderated by order), and C × O (which reflects a main effect of session given the nature of our counterbalanced design).

We used a stepwise approach for model fitting. We started fitting a model that included the intercept and all combinations of effects and (higher-order) interactions. As an initial step, we only added a random intercept (per participant) to this model. Redundant fixed effects were removed iteratively in the following way: we sorted all fixed effects of the model by descending order (highest-order interactions on top) and then by descending p-value, and determined whether removing the first term in this order significantly impaired the model fit of the model using a likelihood ratio test (Chi-square of old versus new model > .05). If the model fit was not significantly diminished, we removed the effect from the model and repeated the elimination steps above until the model could no longer be simplified without significantly reducing explanatory power. Essential terms (see above) were never considered for elimination.

As a final step, we added several random slopes to the model. Because all analyses were run on aggregated data for each cell, the number of observations was limited and although it has been recommended to keep the random effects structure maximal (Barr et al., 2013), these models often result in overparameterized models that fail to converge (Bates, Kliegl, et al., 2015). We, therefore, used a random effects structure that only reflected the essential components used in the fixed effect structure without including additional interaction terms that could potentially lead to convergence failure. All models applied, therefore, included random slopes for all effects T, C, E, and O, as well as for the two-way interaction effects T × C, C × E, T × O, and C × O. We report the parameter estimates of this model.

For some dependent variables, one or two additional within-subject categorical predictors (factors, abbreviated as f) were available, and these were included in the model too using sum-coding (see full reports in the Supplementary Material). For example, midline EEG was recorded over five electrodes (f1 with five levels) and was obtained separately for the three tasks (f2 with three levels). In those cases, the initial model again estimated the full-factorial design and included the intercept and all combinations of effects and (higher-order) interactions, and we used the same approach as described above.

In case the T, C × E and/or T × C terms were involved in higher-order interactions with a factor (e.g., a significant

T×C×O condition), models were fitted again, but now separately for each level (e.g., for both levels of O separately), again removing redundant terms and adding random effects as described above. This approach allowed us to test the three hypotheses indicated above for specific subsets of the data (e.g., both order groups).

We used the lmer function from the lme4 package version 1.1.33 for all statistical analyses (Bates, Mächler, et al., 2015). All reported *p*-values in the tables derive from the anova function from the lmerTest package version 3.1.3, applying type III analysis of variance using Satterthwaite's method (Kuznetsova et al., 2017). Line graphs show estimated marginal means and their confidence intervals based on the predictors T, C, and E, and their interactions. We used the ggemmeans function of the ggeffects package version 1.2.2 to calculate these (Lüdecke, 2018). Model estimates and their 95% confidence intervals were plotted using the plot_model function of the sjPlot package version 2.8.14 (Lüdecke, 2021).

The significance levels were established at a two-tailed alpha of .05. Given the mass univariate approach applied in this study, we also calculated *p*-values corrected for multiple comparisons to limit the chance of reporting false positives, using the false discovery rate approach (Benjamini & Hochberg, 1995). For each term in the model, correction was applied separately to all dependent variables that belong to the same clusters (see Tables 1 and S1 for an overview of these clusters).

We also performed several focused correlational analyses (see Results). These correlational analyses were applied on the estimated random slopes of the local and global effects from the respective model. Prior to correlational analyses, the data were deconfounded by centering the slopes separately for both order groups. In the correlational analyses we also applied the FDR method to correct for multiple comparisons. Finally we applied within-subject mediation analyses using the SPSS macro MEMORE v2.1 (using 10,000 samples to determine bootstrap confidence intervals) based on the estimated intercepts and random slopes of the local effects of the respective variables (Montoya & Hayes, 2017).

3 | RESULTS

3.1 | Effects of time-on-task and the effects of posture

An overview of the main findings for all dependent variables, clustered for self-report, facial EMG, cardiac, neural, behavioral, and computational modeling data, is provided in Table 1. This table features the statistical tests (Type III ANOVAs) of our three focal hypotheses, that is, regarding the effect of time-on-task (time), as well as the local and global effects of posture. Table S2 provides a complete overview of the significance level of all (interaction) effects. In case a significant focal effect was moderated by another factor in the model, such as order, this is indicated in italics, and we then repeated the analysis for each level of this moderator. These findings are discussed in more detail in the supplementary materials. When effects of posture were significantly moderated by another factor, we discuss these effects in the main text as well. Descriptive descriptives for all dependent variables are available in Tables S3–S8.

Below, we highlight the key findings for each cluster. We focus on results that survived corrections for multiple comparisons, using the false discovery rate (FDR) correction method that was applied within each cluster and for each hypothesis separately.

3.1.1 | Self-report data

Replicating earlier work from lab studies on mental fatigue, in the prolonged-sitting session, participants reported increased task averseness and tiredness and decreased task engagement and arousal over time (all $p_{\text{corrected}} < .001$; Table 1). As Figure 2 shows, a standing posture acutely improved arousal ($p_{\text{corrected}} = <.001$) and tiredness ($p_{\text{corrected}} = .006$). Self-reported effort required to perform well on the cognitive tasks (effort costs) was also reduced by a standing posture ($p_{\text{corrected}} = .040$; Figure 3a). Note that for effort costs (Figure S2), tiredness (Figure S3), and task engagement (Figure S4), time-on-task effects were significantly moderated by order, and subsequent analyses for the first two only revealed the time-on-task effect in the group of participants that underwent the Alternation Posture condition in the earlier session, perhaps reflecting a transfer effect from the first (more engaging) session (see supplementary text for more details). Credible global effects of posture were not observed.

3.1.2 | Facial electromyography of the corrugator supercilii muscle

Consistent with the reduced effort costs observed at the subjective level, activity of the corrugator supercilii muscle, a physiological measure of effort costs measured using facial EMG, was reduced locally ($p_{\text{corrected}} = <.001$; see Table 1 for more details), that is, when participants were standing in comparison to sitting (see Figure 3b). In addition, EMG activity reduced with time on task ($p_{\text{corrected}} = .034$).

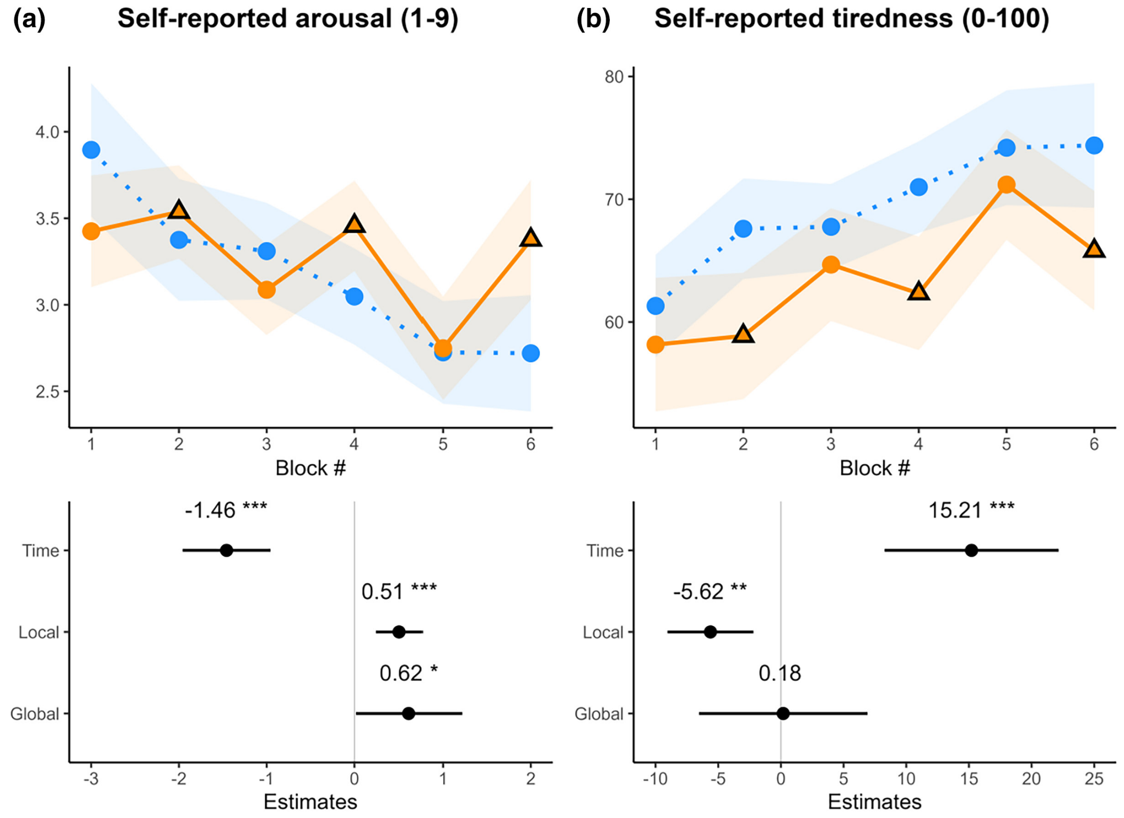

FIGURE 2 Upper panels: Effects of the Prolonged Sitting condition (blue) and the Alternating Posture condition (orange) across the 2-h testing period spanning six blocks. Upper panels show estimated marginal means and 95% confidence intervals. Sitting-posture blocks are represented by circles, while standing-posture blocks are represented by triangles. Lower panels show model estimates and 95% confidence intervals of triangles for the three focal effects: (1) the linear effect of time across the six blocks in the Prolonged Sitting condition (time-on-task effects; effect of Time in the model), (2) the acute effect of standing versus sitting in the Alternating Posture condition contrasted with the effect of odd-numbered versus even-numbered blocks in the Prolonged Sitting condition (zigzag-shaped effects; effect of Condition × Odd–Even Block in the model), and (3) the global effect of alternating versus prolonged sitting indicated by the change in the slope during the sitting blocks (effect of Condition × Time in the model). FDR-corrected p-values are reported in Table 1.

3.1.3 | Cardiac activity

Cardiac data are presented in Figure 4. Time-on-task reduced heart rate ($p_{corrected} = <.001$; see Table 1 for details) and increased heart rate variability ($p_{corrected} = <.001$), suggesting that sitting for 2 h diminished cardiac activity over time. Confirming earlier work, a standing posture acutely increased heart rate ($p_{corrected} = <.001$) and decreased heart rate variability ($p_{corrected} = <.001$), hinting at a combination of increased sympathetic and decreased parasympathetic activity. We also replicated the increase in RZ interval during standing ($p_{corrected} = <.001$) reported earlier (Houtveen et al., 2005), which should, however, not be interpreted as reduced sympathetic arousal because it is confounded by loading effects (i.e., it likely reflects an afterload effect due to mean arterial pressure increases).

Posture was also shown to have a cumulative effect on heart rate ($p_{corrected} = .031$) and heart rate variability ($p_{corrected} = <.001$). Heart rate variability showed a steeper increase in the sitting (odd-numbered) blocks with time in the Alternating Posture condition than in the Prolonged Sitting condition, whereas the opposite pattern, though numerically much smaller, was observed for heart rate. This finding suggests that vagal tone increase during sitting is more pronounced when participants stood in the previous block (Figure 4c). The global effect of posture on RZ-interval ($p_{corrected} = <.001$) was moderated by task order and likely reflected a transfer effect from the first to the second session (see Figure S5).

3.1.4 | Neural oscillations

In line with self-reported arousal levels, our analysis of the neural oscillation data, obtained through Fourier analyses of EEG data obtained at the midline during task performance, consistently showed that the power of alpha

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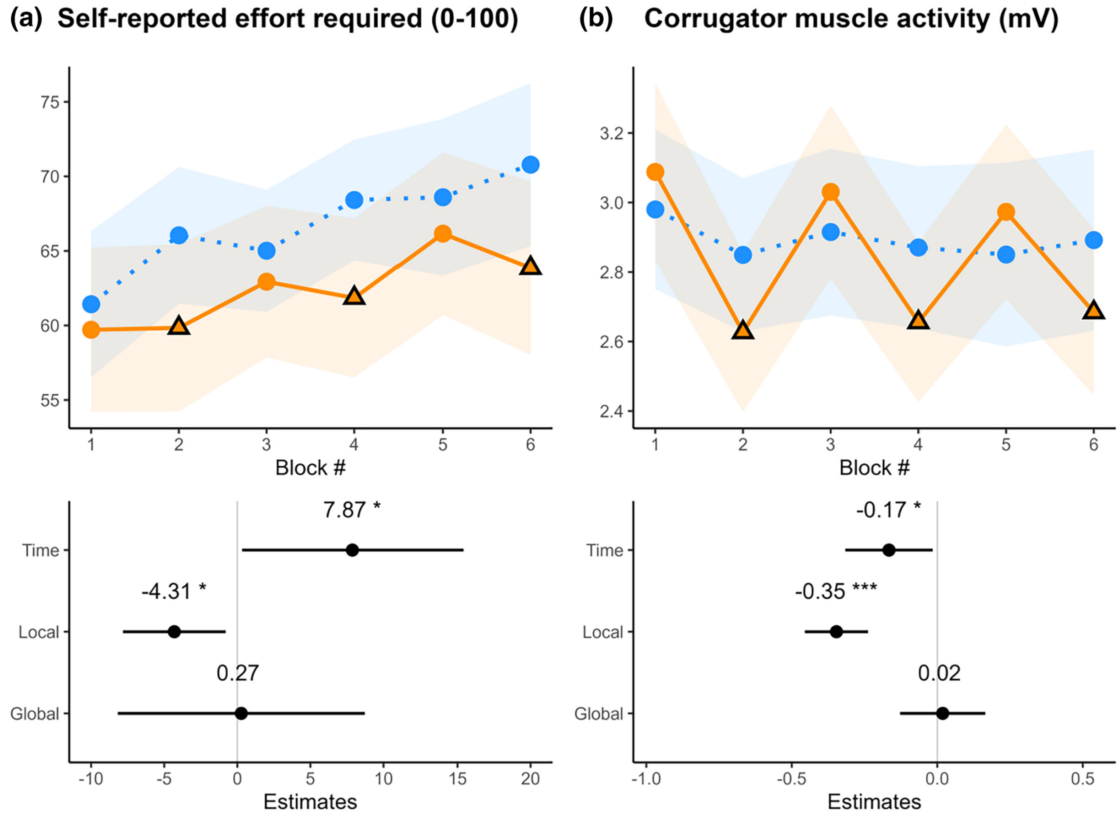

FIGURE 3 Upper panels: Effects of the Prolonged Sitting condition (blue) and the Alternating Posture condition (orange) across the 2-h testing period spanning six blocks. Upper panels show estimated marginal means and 95% confidence intervals. Sitting-posture blocks are represented by circles, while standing-posture blocks are represented by triangles. Lower panels show model estimates and 95% confidence intervals of the three focal effects (for more details, see caption Figure 2). FDR-corrected p-values are reported in Table 1.

(8–12 Hz) oscillations, which serves as an inverse indicator of neural arousal, increased over time ($p_{\text{corrected}} = <.001$; see Table 1 for details), and acutely decreased when participants were in a standing position ($p_{\text{corrected}} = .004$; Figure 5). Delta power (1–4 Hz) also showed an increase with time-on-task ($p_{\text{corrected}} = .028$). No credible effects were observed in the theta (4–8 Hz) and beta (12–30 Hz) ranges.

3.1.5 | Executive function and the general performance

Effects on the main executive function outcomes are displayed in Figure 6. Working memory precision, inhibition (flanker interference effects), and cognitive flexibility (task switch costs) were not strongly affected by time or posture. The apparent zigzag effect of even versus odd-numbered blocks is likely attributable to noise, and this effect was not significant in any of the measures (Table S2). Critically, the only posture-related effect observed in behavior that reached significance was the acute standing-induced improvement of overall performance speed on the flanker task (i.e., collapsed across the two congruency levels), as shown in Figure 7a ($p_{\text{corrected}} = <.001$; see Table 1 for details). This measure was also sensitive to time-on-task ($p_{\text{corrected}} = <.001$).

3.1.6 | Drift diffusion model parameters

To uncover the cognitive processes underlying flanker speed improvement due to postural changes, we fitted the drift diffusion model (Wagenmakers et al., 2007) to our behavioral data. This approach considered RT, accuracy, and their distributions, enabling us to disentangle the effects on the speed of evidence accumulation (represented by the drift rate parameter v), impulsivity (captured by the boundary-separation parameter a), and other processes unrelated to the decision itself (accounted for by the nondecision time parameter Ter). As Figure 7b,c shows, results revealed that posture locally sped up nondecision time Ter ($p_{\text{corrected}} = .003$; see Table 1 for details), suggesting an overall improvement in mere perceptual and/or motor processes unrelated to the decision itself. Critically, we also observed

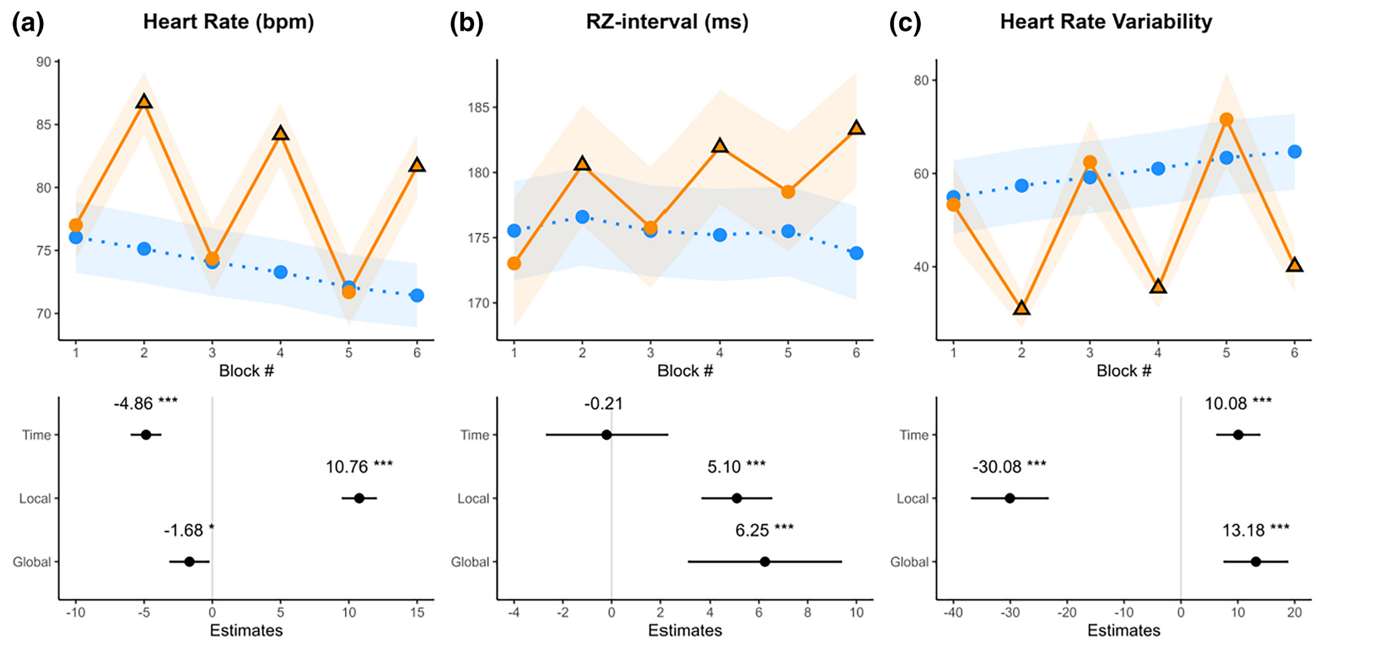

FIGURE 4 Upper panels: Effects of the Prolonged Sitting condition (blue) and the Alternating Posture condition (orange) across the 2-h testing period spanning six blocks. Upper panels show estimated marginal means and 95% confidence intervals. Sitting-posture blocks are represented by circles, while standing-posture blocks are represented by triangles. Lower panels show model estimates and 95% confidence intervals of the three focal effects (for more details, see caption Figure 2). FDR-corrected p-values are reported in Table 1.

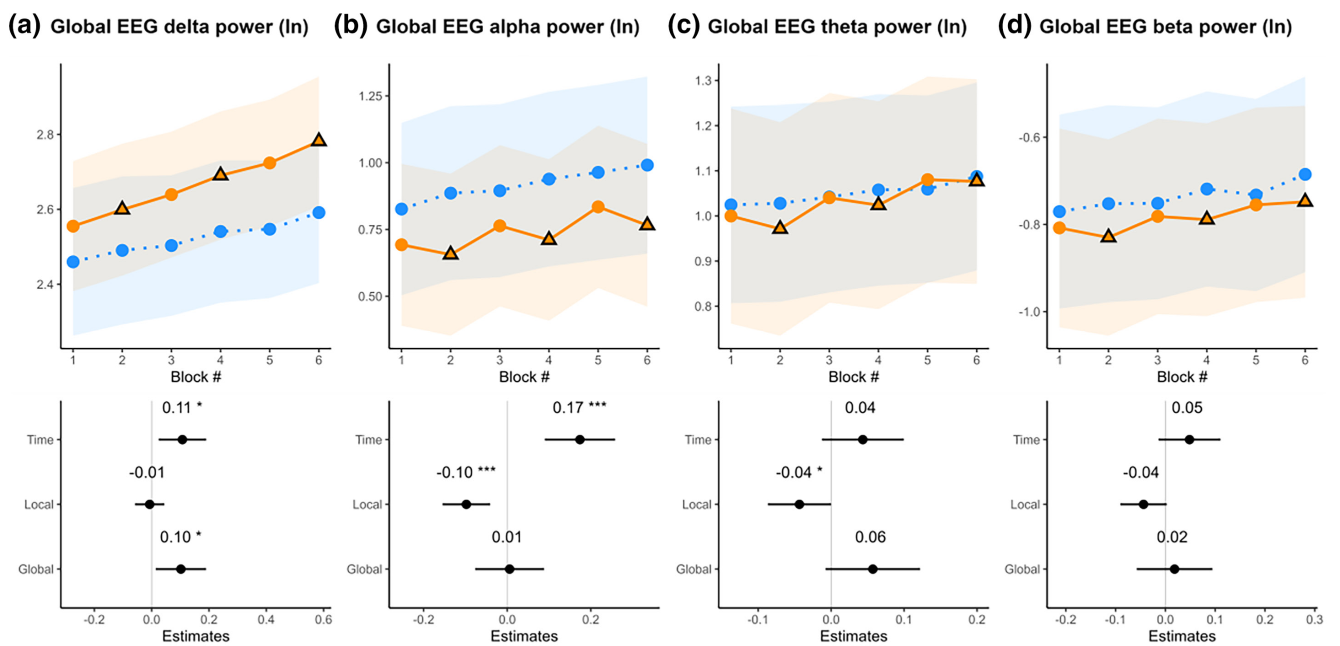

FIGURE 5 Upper panels: Effects of the Prolonged Sitting condition (blue) and the Alternating Posture condition (orange) across the 2-h testing period spanning six blocks. Upper panels show estimated marginal means and 95% confidence intervals. Sitting-posture blocks are represented by circles, while standing-posture blocks are represented by triangles. Lower panels show model estimates and 95% confidence intervals of the three focal effects (for more details, see caption Figure 2). FDR-corrected p-values are reported in Table 1.

an improvement in drift rate v ($p_{\text{corrected}} = .007$), suggesting enhanced speed of cognitive processing. Thus, these parameters together account for the decreased RT observed during standing versus sitting. In addition, the drift rate parameter also significantly decreased with time-on-task ($p_{\text{corrected}} = <.001$).

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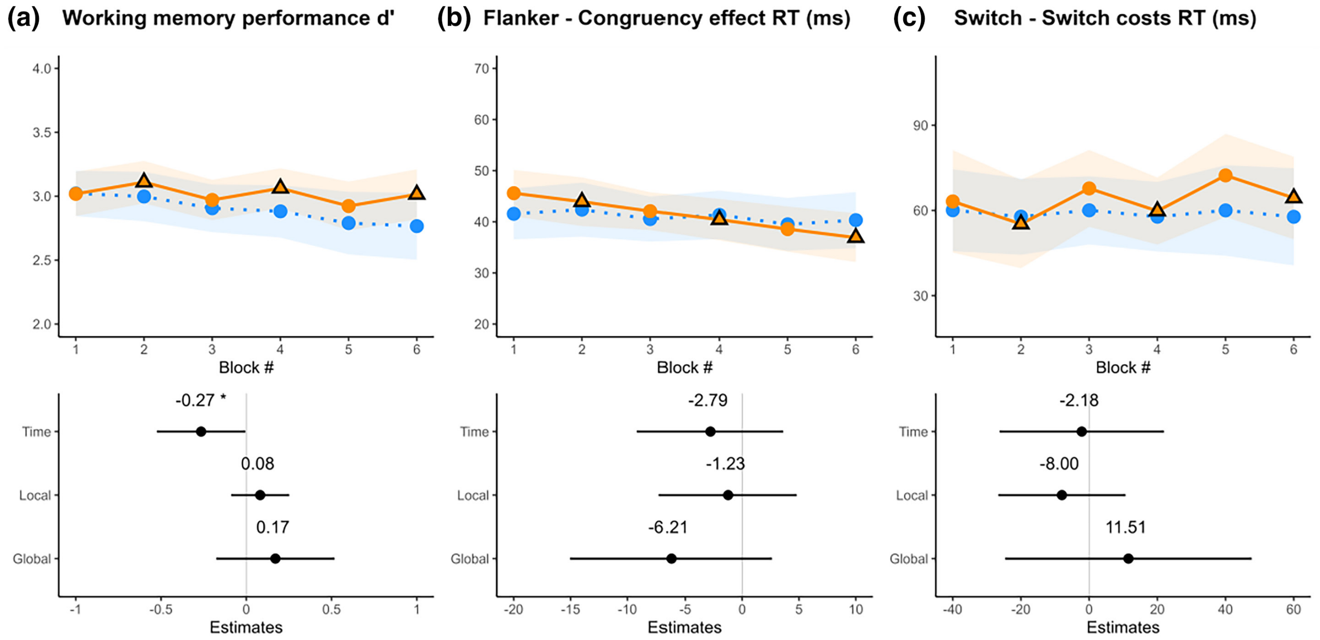

FIGURE 6 Upper panels: Effects of the Prolonged Sitting condition (blue) and the Alternating Posture condition (orange) across the 2-h testing period spanning six blocks. Upper panels show estimated marginal means and 95% confidence intervals. Sitting-posture blocks are represented by circles, while standing-posture blocks are represented by triangles. Lower panels show model estimates and 95% confidence intervals of the three focal effects (for more details, see caption Figure 2). FDR-corrected *p*-values are reported in Table 1.

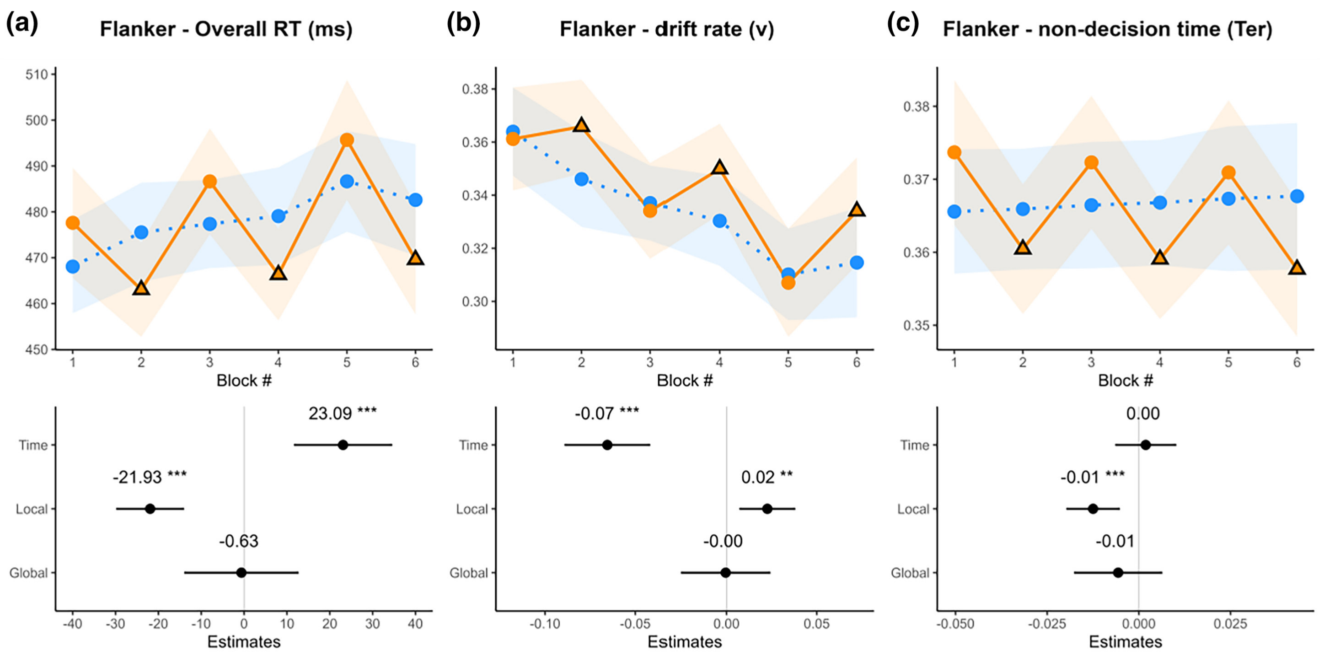

FIGURE 7 Upper panels: Effects of the prolonged sitting condition (blue) and the alternating posture condition (orange) across the 2-h testing period spanning six blocks. Upper panels show estimated marginal means and 95% confidence intervals. Sitting-posture blocks are represented by circles, while standing-posture blocks are represented by triangles. Lower panels show model estimates and 95% confidence intervals of the three focal effects (for more details, see caption Figure 2). FDR-corrected *p*-values are reported in Table 1.

3.2 | Confirmatory meditation analyses

We tested two serial mediation models based on the hypothesis that standing improves cognitive performance via a two-step process involving heart rate increases (mediator 1), which in turn decreases alpha oscillations (mediator 2). This mediation model was applied to both drift rate and nondecision time. No significant mediation was observed for drift rate (indirect effect 1 = −0.0036, *SE* = 0.0082, 95% CI = [−0.0195, 0.0126], indirect effect 2 = 0.0131, *SE* = 0.0103, 95% CI = [−0.009, 0.0317], indirect effect 3 = −0.0015, *SE* = 0.003, 95% CI = [−0.0084, 0.0036]. sum of indirect effects = 0.008, *SE* = 0.0133, 95% CI = [−0.0194, 0.0333]). For nondecision time we observed a link with alpha power reductions, but no other mediations were observed (indirect effect 1 = −0.0005, *SE* = 0.0028, 95% CI = [−0.0057, 0.0054], indirect effect 2 = −0.0127, *SE* = 0.0057, 95% CI = [−0.023, −0.0018], indirect effect 3 = 0.0015, *SE* = 0.0023, 95% CI = [−0.003, 0.0064], sum of indirect effects = −0.0117, *SE* = 0.006, 95% CI = [−0.022, 0.0009]).

3.3 | Exploratory correlational and mediation analyses

In order to reveal whether the effects of posture at the different levels were related, we conducted a few targeted exploratory correlation analyses. As illustrated in Figure 8 (**purple overlay**), we first tested whether the acute, local effects of posture-induced arousal as measured at different levels were related. We only revealed a significant correlations between self-reported and neural arousal effects, suggesting that arousal measured at different levels reflect partially separable constructs. We repeated this approach to investigate the link between self-reported and fEMG level of effort costs (Figure 8, **green overlay**). This analysis revealed a positive correlation between acute posture effects on self-reported effort and tiredness. Third, we tested whether individual differences in the local effects on arousal and effort costs could predict the observed local improvement of evidence accumulation and nondecision time (Figure 8, **orange overlay**) to identify candidate mediating variables between our body posture intervention and cognitive outcomes. We observed that self-reported arousal increase predicted improved drift rate whereas neural alpha power reductions predicted quicker nondecision time. Finally, global effects on HRV (Figure 8, **blue overlay**) were predicted by local effects on HRV, suggesting that increased HRV over time by alternating posture is more pronounced in individuals that show relatively larger local posture-induced HRV reductions.

Based on the identified candidates for moderators in the analysis above, we ran two additional data-driven, exploratory within-subject mediation models. These models tested (1) whether self-reported arousal mediated

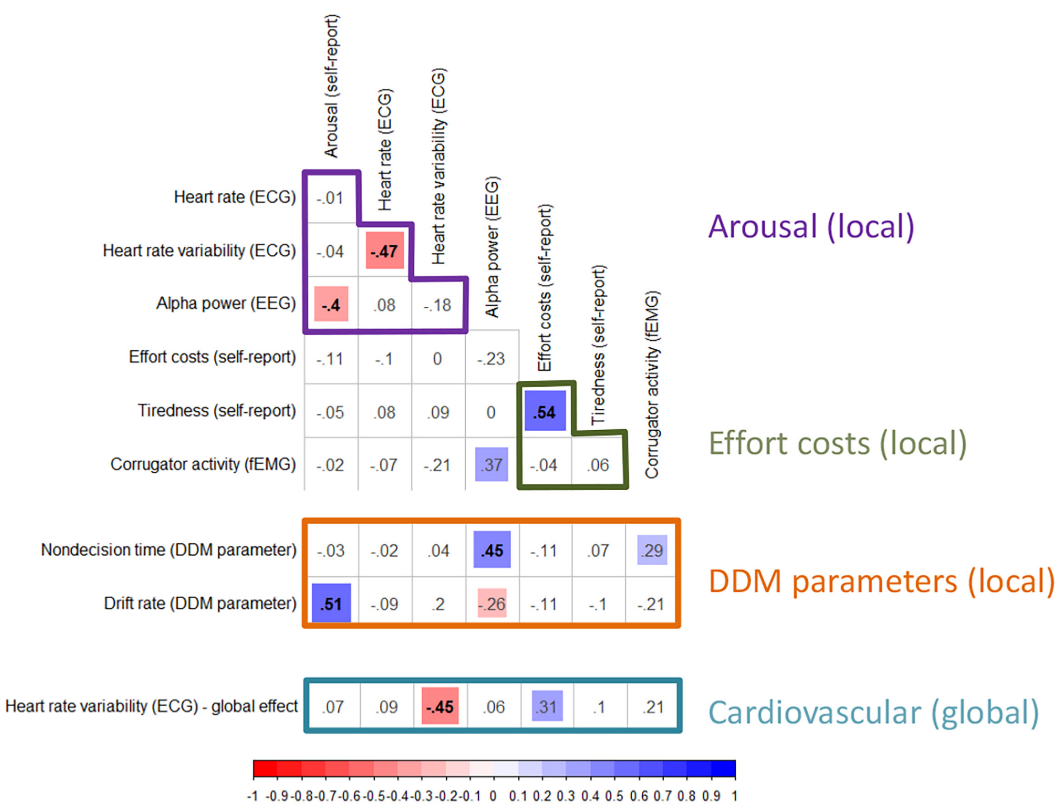

FIGURE 8 Targeted correlations on posture effects for arousal, effort costs, drift diffusion model parameters, and cardiovascular activity. Colored cells indicate significant correlations based on uncorrected *p*-values. Correlations that survive FDR-correction are provided in bold.

the acute posture effects on improved drift rate and, (2) whether alpha power reductions mediated the acute posture effects on reduced nondecision time. Self-reported arousal indeed mediated the posture-driven increases in drift rate (indirect effect = 0.0115, SE = 0.005, 95% CI = [0.0016, 0.021]), in the absence of a direct effect (direct effect = 0.0111, SE = 0.0064, 95% CI = [−0.0018, 0.024], $t(43) = 1.7362$, $p = .0897$; total effect = 0.0226, SE = 0.0031, 95% CI = [0.0164, 0.0288], $t(45) = 7.3623$, $p < .001$). Likewise, alpha power reductions mediated the posture-driven reduced nondecision time (indirect effect = −0.0108, SE = 0.0049, 95% CI = [−0.0189, −0.0012]) in the absence of a direct effect (direct effect = −0.0019, SE = 0.0031, 95% CI = [−0.0082, 0.0043], $t(42) = -0.6282$, $p = .5333$; total effect = −0.0127, SE = 0.0014, 95% CI = [−0.0155, −0.0099], $t(44) = -9.2076$, $p < .001$).

4 | DISCUSSION

This study used a comprehensive, multi-method approach to investigate the potential beneficial cognitive effects of using a sit-stand desk by studying the local and global effects of alternating between sitting and standing postures compared to a prolonged sitting condition on multi-modal measures of arousal, effort costs, and executive function. Our main findings are that standing relative to sitting yielded local (acute) (1) increases in arousal at the self-report, neural, and cardiac level, (2) reductions in effort costs at the physiological and subjective level, and (3) improved cognitive performance in the flanker task, that could be attributed to a facilitation of nondecision time and the acceleration of evidence accumulation. In addition, we observed global, cumulative benefits of an alternating body posture on cardiac activity. These effects were observed in a task that induced task-related mental fatigue throughout a testing period of 2 h in the prolonged sitting condition, in which we replicated earlier reported subjective effects (Boksem et al., 2005; Hopstaken et al., 2015a; Lorist et al., 2005). We did not find evidence supporting the hypothesized link that posture-induced performance improvements occurred via sympathetic arousal which in turn should increase neural arousal (Thibault et al., 2014). Exploratory correlation analyses revealed that posture effects on arousal and effort were not strongly related across different levels. Exploratory mediation analyses revealed that subjective arousal mediated drift rate improvements, while neural arousal mediated nondecision time. Below, we will discuss the scientific and practical implications of our findings.

Our study revealed performance benefits of standing that were limited to overall performance in the flanker task (see also Abou Khalil et al. (2023)). Utilizing drift diffusion modeling, we revealed that this effect was related to reduced nondecision time, suggesting that a standing posture speeds up perceptual or motor processing. However, in addition to these effects, we observed that a standing posture also increased drift rate, implying that posture also speeds up central decision-making processes. Our exploratory mediation analysis suggested that these drift rate increases were directly linked to posture-related subjective arousal increases. This suggests that arousal increases may play a causal role in the speed of evidence accumulation in relatively simple cognitive tasks. This conclusion is consistent with recent findings that have linked posture-induced drowsiness to decreases in the speed of evidence accumulation in perceptual decision-making tasks (Jagannathan et al., 2022). At the neural level, these effects could have been driven by arousal-linked brain states. The observed attenuation of global alpha power during standing in our study is consistent with earlier work suggesting that sleepiness and alpha power are related (Torsvall & Åkerstedt, 1987), and that indirect stimulation of the LC-NE system increases pupil dilation and attenuates alpha oscillations (Sharon et al., 2021). Animal work has linked locomotion and arousal to gain modulation of neurons in perceptual regions, which provides a mechanistic account for the observed effects (Aston-Jones & Cohen, 2005; Ferguson & Cardin, 2020). However, in our study, we failed to establish a clear connection between neural oscillations and drift rate and instead observed that alpha power mediated nondecision time. Furthermore, our confirmatory two-step serial mediation analyses did not provide any evidence for a mediating effect of alpha oscillations via heart rate increases. This shows that it is difficult to directly relate sympathetic arousal to neural arousal. One possible explanation for this difficulty is that our study lacked sufficient power to detect subtle differences between individuals. Additionally, using heart rate as a proxy for sympathetic arousal is problematic since it is also influenced by the parasympathetic system. Moreover, posture-induced enhancement may involve other pathways, such as the vestibular reflex (Caldwell et al., 2000). Therefore, future research should incorporate additional physiological measures (including blood pressure, see Cole, 1989) to uncover the mechanisms underlying the positive effects of posture on the decision-making process. In addition, our correlational findings require independent replication in larger sample sizes.

Consistent with earlier suggestions that using sit-stand tables do not negatively impact higher-level cognitive function in workplace settings, we also did not find evidence for impairment of executive function when participants stand. This finding reinforces similar conclusions in a recent review (Sui et al., 2019). However, unlike some earlier reports (Bhat et al., 2022; Dodwell et al., 2019; Rosenbaum et al., 2017; Smith et al., 2019), we could not identify beneficial effects of standing on executive functions either. These null-findings are in line with recent failures to replicate posture-related improvements in executive function (Caron et al., 2020; Ohlinger et al., 2011; Straub et al., 2022). The absence of observed benefits in executive functions associated with standing calls for future studies with larger sample sizes and refined experimental designs.

While our observations did not reveal improvements in executive functions, it is important not to discount the potential benefits associated with adopting an alternating posture, as we did observe clear advantages at the subjective and physiological levels. First, perceived effort required to perform the cognitive tasks correctly as well as self-reported mental fatigue were reduced when participants were standing. Second, activity of the corrugator supercilii (the "frowning muscle") that is thought to track negative affect (Larsen et al., 2003) and the costs incurred by tasks requiring effortful control (Berger et al., 2020; Boxtel et al., 1993; Devine et al., 2023), was decreased while standing. Although we did not include a control measurement recording activity of a different facial muscle, it is unlikely that the fEMG effect merely reflects a broad musculoskeletal effect on facial muscle activity also observable outside the context of mental work because earlier work did not observe this effect in a resting state (Thibault et al., 2014). Taken together, these findings suggest that a standing posture reduces effort costs, possibly because of the upregulated arousal level our manipulation induced (Massar et al., 2019). A recent surge of findings has established the important functional and neurocomputational role of effort costs as they may govern the decision to engage in mental work (Boksem & Tops, 2008; Kurzban et al., 2013; Massar et al., 2018; Shenhav et al., 2017). Although we did not observe credible evidence for effects on task engagement in our study using a relatively short time frame, it is likely that reduced effort costs in the long term may help to stay engaged in a task, which may explain the increase in productivity associated with the use of sit-stand tables observed in some studies (Dupont et al., 2019; Sui et al., 2019).

On a more theoretical note, our observation that perceived effort costs increases with time-on-task, and that posture-induced arousal can reduce it, is consistent with an account built on motivational intensity theory (Brehm & Self, 1989; Richter et al., 2016) that has predicted that perceived difficulty increases with mental fatigue (Wright et al., 2013). This theory also predicts concomitant fatigue-related increases in beta-adrenergic cardiovascular measures of effort mobilization, for relatively easy tasks, as has been shown repeatedly (e.g., Mlynski et al., 2021; Wright et al., 2013). Our dataset allowed us to use the RZ interval as a proxy for measuring this beta-adrenergic cardiac effort, as it is closely linked to the cardiac pre-ejection period (Lozano et al., 2007). However, we were unable to identify a time-on-task effect in the RZ interval, which prevented us from confirming this prediction with our data, at least when using a proxy of the pre-ejection period. It is important to note that we were unable to interpret the local effect of posture on the RZ interval, as previous work using blood pressure measurements has revealed that it is confounded by the afterload effect caused by an increase in mean arterial pressure when standing (Houtveen et al., 2005). Moreover, given that we did not include blood pressure measurements in our setup we were unable to investigate fatigue-related effects on cardiac effort using systolic blood pressure.

Furthermore, adopting an alternating posture was found to be linked with increases in heart rate variability over time. Since heart rate variability primarily reflects the activity of the parasympathetic, or rest-and-digest, branch of the central nervous system, this finding suggests that incorporating alternating posture into daily routines may contribute to a healthier lifestyle. While sedentary behavior has been associated with increased markers of cardiovascular disease (Katzmarzyk et al., 2009), there is currently limited evidence supporting the cardiovascular health benefits of using a sit-stand desk (Chambers et al., 2019). One possible explanation for this is the absence in the existing literature of fine-grained analyses that take into account the time-course of cardiac effects. In fact, our 2-h experiment revealed intricate temporal dynamics in cardiac effects. Specifically, we found that standing temporarily reduced heart rate variability, but this was followed by a more pronounced cardiac recovery during the subsequent sitting period. This suggests that while transitioning from sitting to standing may momentarily decrease vagal tone, alternating between these postures in the long run can have cumulative positive effects on vagal tone. Given that vagal tone serves as an indirect marker of reduced bodily stress (Thayer et al., 2012), our findings align with a recent pilot study that demonstrated reduced levels of the stress hormone cortisol associated with standing (Gilson et al., 2017). Collectively, these results provide insights into the potential physiological benefits of incorporating alternating postures, suggesting that it may have a positive impact on both cardiovascular health and stress reduction.

We acknowledge certain limitations in our current work. First, our comprehensive approach, drawing from a vast and diverse literature, enabled us to analyze a wide range of measures at multiple levels, employing a predominantly data-driven, exploratory approach. While this has yielded fresh insights with potential practical implications, it does not definitively confirm or refute predictions derived from a specific theory. Constructs such as arousal and effort costs possess multidimensional aspects, necessitating a multi-level analysis for an adequate description (Neiss, 1988). Integrating these multi-dimensional constructs into theory remains an ongoing challenge for the field of psychological science (Fried, 2020; Muthukrishna & Henrich, 2019). Nonetheless, we remain optimistic that the extensive findings presented here will help to inspire the formulation of more precise and testable theories in the future, thereby advancing our understanding of the biological mechanisms underlying posture-induced performance benefits.

Another limitation of the present study is that we included a student sample of young adults who performed a battery of cognitive tasks. There is some evidence that fatigue-reducing effects of alternating body posture are stronger in less fit populations, as observed in overweight individuals (Thorp et al., 2011). It is thus possible that our findings underestimate the beneficial effects of standing in the general population. Arousal-related benefits remain to be shown in other samples, for example, populations with underdeveloped or compromised executive functions, such as school children and older adults (Zelazo et al., 2004). Understanding the mechanisms that drive beneficial cognitive effects in these populations might also help to develop fully tailored interventions to reduce sedentary behavior.

Third, we selectively observed performance improvement in the flanker task and not in the switch task and the working memory task. This may suggest that evidence accumulation improvements in decision-making processes are task-specific. Alternatively, the effects of posture-induced arousal might have interacted with the overall level of task difficulty. On this account, posture-induced arousal might be particularly beneficial for tasks that are relatively easy, which is consistent with studies that suggest an inverted-U relationship between activity-induced arousal and performance (Tomporowski & Ellis, 1986).

Finally, in line with earlier recommendations (Buckley et al., 2015), our participants stood for a maximum of about 20 min per bout, and it is well-known that standing can induce mental fatigue when it has to be maintained for longer time periods (Hasegawa et al., 2001; Schraefel et al., 2012). Altogether, these findings suggest that future research needs to determine the boundary conditions under which posture-induced improvements occur, an issue that echoes earlier debates about the nonlinear effects of exercise-induced arousal on cognition (McMorris & Graydon, 2000; Tomporowski, 2003) (see also, Blain et al., 2019). From an applied perspective, our findings tentatively suggest that participants may process information more efficiently and thus show potential improvements in productivity when standing, but these effects are most likely to occur when tasks are relatively easy, and bouts of standing are short.

In conclusion, our study provides evidence that participants who regularly alternate between standing and sitting postures experience increased levels of arousal while standing, which could be attributed to neural and cardiac effects. Additionally, we observed limited benefits in cognitive performance. Furthermore, adopting a standing body posture resulted in reduced physiological and self-reported costs associated with cognitive work, along with an increase in vagal tone over time compared to prolonged sitting. These findings indicate that regularly transitioning from a sitting to a standing posture could potentially lead to a more pronounced engagement of the parasympathetic rest-and-digest system. Our results tentatively suggest that participants process information more efficiently and demonstrate improved arousal when standing, particularly for relatively easy tasks and short bouts of standing. Overall, this study contributes to the growing body of literature on the cognitive benefits of using a sit-stand desk and supports its active implementation for promoting health and productivity in the workplace.

AUTHOR CONTRIBUTIONS

Henk van Steenbergen: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; software; validation; visualization; writing – original draft; writing – review and editing. **Tom F. Wilderjans:** Formal analysis; methodology; software; writing – review and editing. **Guido P. H. Band:** Conceptualization; methodology; writing – review and editing. **Sander T. Nieuwenhuis:** Methodology; writing – review and editing.

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on Brain & Cognition, 2022; TeaP (Tagung experimentell arbeitender Psychologen), virtual, 2022; ESCAN conference, virtual, June 2021.

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no competing interests.

DATA AVAILABILITY STATEMENT

All raw and preprocessed data as well as all R analysis scripts are available at https://osf.io/nxed4/?view_only=5adee0454d8e4df7bb0bbafbdf30d9de. This study was not preregistered.

DATA TRANSPARENCY APPENDIX

Event-related analyses of the cardiac response to errors during the prolonged sitting condition have been published separately elsewhere (Spruit et al., 2018).

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT in order to improve language and readability. After using this toolservice, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

ORCID

Henk van Steenbergen https://orcid.org/0000-0003-1917-6412

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Data S1.

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