Psychophysical and autonomic neural correlates of acute mental fatigue induced by prolonged attention-demanding tasks

Doctoral (PhD) thesis

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Introduction

Mental fatigue is an everyday feeling that usually results from prolonged cognitive activities requiring sustained attention and cognitive control. Given that mental fatigue (hereafter: fatigue) has a detrimental effect on a wide range of cognitive functions, for example, selective attention or working memory, it has been suggested that fatigue is one of the primary risk factors for accidents, injuries and medical errors. In line with this, fatigue has been estimated to be a risk factor in approximately 40% of road crashes, which is comparable that of alcohol intoxication (Fletcher, McCulloch, Baulk & Dawson, 2005). Among junior doctors, 42% of the 1366 respondents reported fatigue-related clinical errors (Gander, Purnell, Garden & Woodward, 2007), indicating that the presence of fatigue has a substantial negative impact on medical professionals' ability to provide high-quality patient care. In addition, a more recent longitudinal study involving almost 16,000 people showed that work-related fatigue caused by repeated exposure to high cognitive demands increases the risk of insomnia symptoms (Skarpsno, Nilsen, Sand, Hagen & Mork, 2020).

It is thus clear that fatigue affects many aspects of life; however, in order to successfully prevent or at least predict its negative consequences, we need to understand the nature of this complex biopsychological phenomenon. Given that both the manifestation of fatigue and the underlying biological and psychological mechanisms highly vary between individuals and environmental conditions (Ackerman, 2011), the scientific investigation of fatigue requires a rather multidisciplinary approach. Consequently, the experiments presented in this paper involved the analysis of data obtained by cognitive psychological research methods as well as physiological measurements. In addition, we also aimed to utilize machine learning algorithms to detect fatigue and predict its severity based on biological signals and other parameters.

2. Aims

2.1. The effects of mental fatigue on the preparation and execution of visually guided pointing movements during sustained attention

Visually guided movements involve two distinct phases: a planning or preparatory phase that usually refers to the period between stimulus presentation and movement initiation, and an execution phase that refers to the interval from movement onset to the successful reach of the target (Elliott, Helsen & Chua, 2001; Woodworth, 1899). The main goal of the first study was to assess the effects of fatigue specific to the two phases of movements. Therefore, in three experiments, we used a mouse-pointing task with high demands on sustained attention to induce fatigue and investigate its effect on movement preparation and execution. Based on previous studies, we hypothesized that movement preparation will be sensitive to the detrimental effects of fatigue. On the other hand, regarding the movement execution phase, we expected participants to execute movements more impulsively (i.e. faster but more erroneously). In Experiment 1, the potential locations of the visual targets were variable and required more complex movements. In Experiment 2, the number of target locations were reduced and only horizontal movements were required to reach the target. In addition, in Experiment 3, auditory cues were used to rule out the potential effects of orientation deficits and decreased phasic alertness on movement preparation and execution.

2.2. Time-on-Task-related changes in autonomic nervous system activity reflected by heart rate variability during prolonged task performance

A large body of the literature has explored the association between fatigue and heart-rate variability (HRV), a measure of autonomic regulation of cardiac activity (e.g. Tran, 2009; Mizuno et al., 2011, 2014; Gergelyfi et al., 2015). Although these studies converge on the notion that HRV is a significant biomarker of fatigue, however, because HRV has many calculable components that have diverse sources (Billman, 2013), the interpretation of the results is inconsistent across studies. As a result, the exact interpretation of the fatigue-HRV relationship is still unclear. In addition, most studies lack the comparison of the fatiguing task with a non-fatiguing condition, however, such comparisons may shed light on which HRV components are sensitive or insensitive to fatigue. Therefore, in the second study, participants were assigned into two groups. One of the groups engaged in a fatiguing bimodal working memory task for 1.5 hours, while the other group viewed documentaries. Our primary aim was to investigate which HRV components change with increasing time on the fatiguing working memory task, while remain unchanged during documentary viewing.

2.3. The effects of fatigue on cross-modal interference in a selective attention task

According to the Modality appropriateness hypothesis, the visual modality is more accurate in the spatial dimension, while the auditory modality is more accurate in the temporal dimension. Thus, when temporal processing is required to successfully perform a task, the auditory modality is preferable. In line with this, Lukas et al. (2014) found that performance on a bimodal temporal discrimination task was better when the target stimulus was an auditory signal compared to when the target was a visual signal. In addition, they found that the interference on the visual processing caused by auditory distractors was higher than the interference on auditory processing caused by visual distractors. In our third study, participants were asked to perform the same bimodal temporal task for 1.5 hours and we hypothesized that performance in the visual trials will decrease with increasing time-on-task, while the auditory modality will be robust against the effects of time-on-task. We also hypothesized that the interfering effect of auditory distractors on visual processing will increase over time. In addition, we aimed to find further empirical support for the HRV-related findings in Study 2.

2.4. Predicting and detecting mental fatigue using machine-learning algorithms trained on HRV data

Previous studies have shown that machine-learning algorithms trained on HRV data can effectively (i.e. with an accuracy of 70-80%) detect mental fatigue (Laurent et al., 2013; Huang et al., 2018). However, these algorithms were trained on relatively small datasets (n = 13 – 35) and for the induction of mental fatigue, only one specific type of cognitive task was used. Therefore, the external validity of these results is limited meaning that the performance of the algorithms cannot be generalized to the broader population. In order to overcome these methodological issues, we combined the datasets (n = 87) of three different fatigue experiments with various cognitive tasks and used machine-learning algorithms to detect the presence of fatigue based on HRV data. In addition, we trained regression models as well to predict the level of subjective fatigue caused by prolonged task performance based on HRV data and other variables.

3. The effects of mental fatigue on the preparation and execution of visually guided pointing movements during sustained attention

3.1. Experiment 1

3.1.1 Methods

Participants

Thirty-one students from the University of Pécs took part in the first experiment as volunteers. Due to technical issues, the data of five participants were excluded. Thus, the final dataset consisted of 26 participants (18 female, aged between 18 and 26 with a mean of 19.77 (SD = 1.58)). All of them reported to have normal or corrected-to-normal vision and none of them reported any health problems. Based on self-report, three of them were left-handed, however, they reported to prefer the right-hand use of the mouse. Prior to the experiment, we estimated the minimum required sample size by using Gpower 3.1. (Faul, Erdfelder, Land & Buchner, 2007). Based on the effect sizes (η_p^2 = .27 – .30) reported in previous studies, the lowest sample size to achieve a statistical power of 90% with an alpha level of 5% was 18.

Task and Stimuli

The visually guided mouse-pointing task was coded and executed by using PsychoPy 3 (version 3.1.5., Peirce, 2007, 2009). Stimuli were presented on a Tobii TX300 integrated monitor with a resolution of 1920 x 1080 pixels, refreshed at 60 Hz. Participants were seated 60 cm from the screen. We used a standard computer mouse positioned for right hand use. Standard Windows 10 mouse sensitivity settings were applied.

Figure 1. schematizes the sequence of a trial. During the whole course of the task, at the centre of the screen, a white fixation cross (25 x 25 pixels) was presented. The target stimulus was a white filled circle (20 pixels in diameter) presented at one of the 16 possible locations. These locations were arranged along two (invisible) concentric circles around the fixation cross. The diameters of the inner circle and the outer circle were 250 and 500 pixels, respectively. On each trial, participants were instructed to fixate and to keep the cursor on the fixation cross until the target stimulus appeared. If they initiated a mouse movement earlier, the fixation cross changed its colour to red and the target presentation was inhibited. The target was presented after a random interval ranging between 500 and 7000 ms drawn from a continuous uniform distribution. Participants were asked to move the cursor onto the target as quickly and as precisely as possible, while time and two-dimensional mouse coordinates were continuously

recorded. The trial was successful if the cursor entered the area of the target stimulus and stayed there for at least 100 ms. If these criteria were fulfilled, then the colour of the target turned to black indicating that the cursor now must be moved back to the fixation cross. Immediately after returning to the fixation cross, a 250 Hz tone was presented for 200 ms via standard loudspeakers and visual feedback about the time required to reach the target was provided for 500 ms, located 50 pixels above the fixation cross. The next trial started after the feedback disappeared.

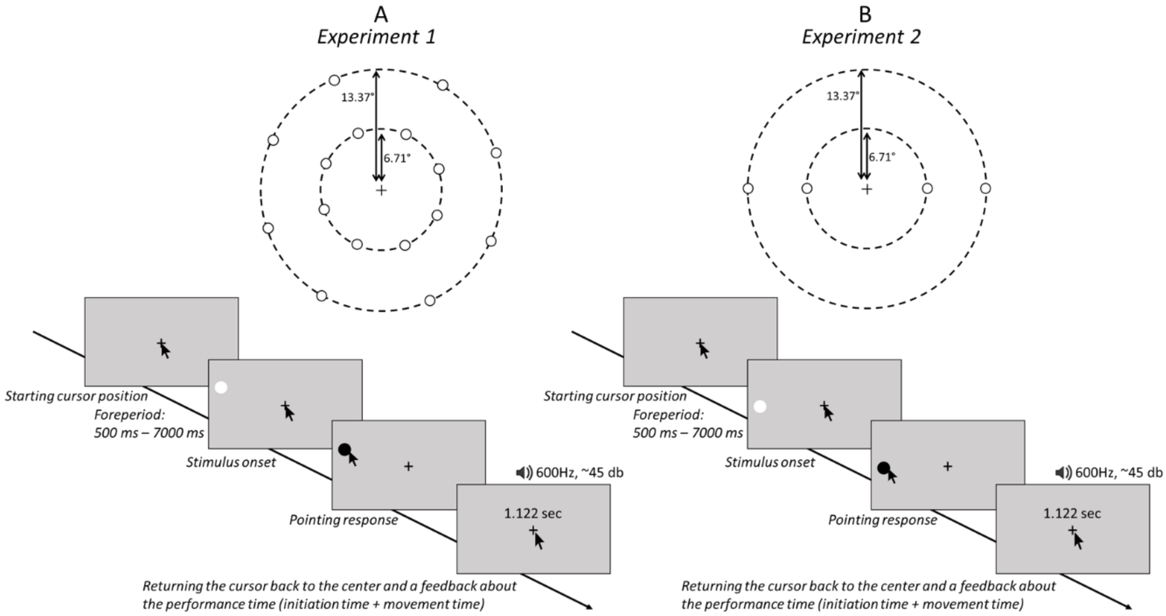

Figure 1. Schematized layout of the target positions and the sequence of trials in Experiment 1 (A) and Experiment 2 (B)

Procedure

Participants were asked to have an adequate sleep on the night prior to the experiment. In addition, they were asked to refrain from consuming alcohol and caffeinated beverages on the day of the experiment. Upon arrival to the laboratory, participants were informed about the general procedure of the experiment and written consent was obtained. Then, sleep duration was estimated by self-report (the mean sleep duration was 7.85h (SD = 1.39)). After that, the pointing task was explained to the participants and they performed 20 practice trials. The practice was followed by a standard 5-point eye-tracking calibration. A chin rest was used to ensure higher accuracy of recording eye movements. Following the calibration, participants were asked to indicate their actual level of subjective fatigue on a 100 mm long visual analogue scale (VAS) presented on the centre of screen. “*No fatigue at all*” was presented on the left side of the scale, while “*Very severe fatigue*” was presented on the right side of the scale. After that, the Time-on-Task phase (ToT-phase) started, which consisted of three blocks of 56 trials. Each block lasted approx. 5 minutes, thus the whole duration of the ToT-phase was approx. 15 minutes. Trials were presented in a pseudorandom order. When the ToT-phase ended, the participants indicated again their actual experience with subjective fatigue on the VAS. After the experiment, the participants were briefed and asked whether they had difficulties at using the mouse and whether they experienced physical discomfort in their hands. None of them reported any difficulties or pain suggesting that task performance was not affected by physical factors.

Analyses of performance measures

In each trial, participants' data files contained the time stamps and x, y coordinates of the cursor. Cursor positions were sampled at 60 Hz. All movement trajectories were aligned to the same initial coordinates ([0,0]; following Spivey & Grosjean, 2005). Euclidean distances travelled between consecutive cursor displacements and velocity for each movement trajectory were extracted. Trajectories of each participant were plotted, and then, visually inspected for unusual patterns (e.g. large amounts of up and down movements, unusual movements resulted from slips of the hand etc.). Only one such trajectory was identified and excluded from further analysis.

Several temporal and spatial (or accuracy-related) mouse-movement metrics were calculated. To assess the movement preparatory phase, initiation time was analysed. Initiation time was defined as the interval between the onset of target presentation and movement initiation (i.e. when the cursor left the fixation cross, thus had been moved by 3 mm).

In order to analyse participants' movement execution, we selected measures that characterize the temporal and spatial profiles of the movement trajectories. For the temporal profile, we calculated movement time (MT) and peak velocity (PV). MT was defined as the interval between movement initiation and target reach. PV was defined as the highest value of velocity during the movement. For the spatial profile, movement error (ME) was selected, which is one of the accuracy measures proposed by MacKenzie and colleagues (2001) and represents the average absolute deviation of the x-y coordinates from the task axis (i.e. the shortest path to the target). In addition, we analysed the ratio of MT and ME (henceforth MT / ME ratio) as an index of speed-accuracy adjustments.

Analyses of eye movements

Eye movements during the whole course of the experiment were recorded by a Tobii TX300 eye tracker with a sampling rate of 120 Hz. The recorded data was exported and processed offline. Missing data (i.e. validity codes higher than 1 provided by the eye tracker) due to blinks and artefacts were linearly interpolated. Fixations were defined using the default settings of Tobii. Trials where participants did not fixate on the fixation cross during stimulus presentation were excluded from further analyses of behavioural performance and eye movement metrics. For the analysis of saccadic latency, only trials with less than 33% of missing data were included. Saccadic latency was defined as the time (in milliseconds) from target onset to the initiation of the first valid saccade toward the stimulus. An eye movement was considered a valid saccade when velocity exceeded 30°/s, acceleration was higher than $8000°/s^2$ and distance was higher than 0.5° (Stigchel et al., 2011). Only saccadic latencies higher than 80 ms were included in the analysis. Finally, fixation instability was computed as the averaged standard deviation of the horizontal and vertical eye position during fixation.

The performance measures and saccadic latency data were subjected to separate repeated measures ANOVAs (rANOVA) with Time-on-Task (the three blocks of trials), Target distance (near vs. far distance). Follow-up rANOVAs or paired t-tests were used to analyse significant interactions and main effects. Pairwise comparisons were adjusted for multiple comparisons using Bonferroni correction.

3.1.2 Results

Figure 2 depicts the results of the six variables analysed to assess the Time-on-Task related changes in mouse-pointing movement. The analysis of subjective fatigue ratings revealed significantly higher fatigue after the task than before, suggesting that the continuous performance of the mouse pointing task enhanced the participants' feeling of fatigue ($t(25) = -3.55$, $p < .01$). In line with our first hypothesis, the analysis of initiation time yielded a significant Time-on-Task effect ($F(2,50) = 12.87$, $p < .001$, $\eta_p^2 = .34$): participants initialized their pointing movement slower with increasing Time-on-Task indicating fatigue-related effects on movement preparation. In contrast to initiation time, the initialization of saccadic eye-movements (i.e. saccadic latency) to the direction of the target showed no change over the task performance period ($F(2,50) = .12$, *n.s.*, $\eta_p^2 = .01$). The lack of Time-on-Task effect on saccadic latencies may imply that the slowing of movement initialization was not predominantly related to the sensory processing deficit of the peripheral target.

For the execution phase of the pointing movement, two variables were significantly affected by Time-on-Task: the movement time ($F(2,50) = 5.98$, $p < .01$, $\eta_p^2 = .19$) and the MT/ME ratio ($F(2,50) = 5.28$, $p < .01$, $\eta_p^2 = .17$). We found that, as a function of Time-on-Task, participants executed the pointing movement faster but not with improving accuracy resulting in a decreased MT/ME ratio. This finding was partly in line with our second hypothesis showing that fatigued participants tend to execute movements more impulsively. Finally, the analysis of fixation instability showed no significant change over time ($F(1,25) = 1.21$, n.s., $\eta_p^2 = .05$). None of the Time-on-Task x Target distance interactions reached the level of significance.

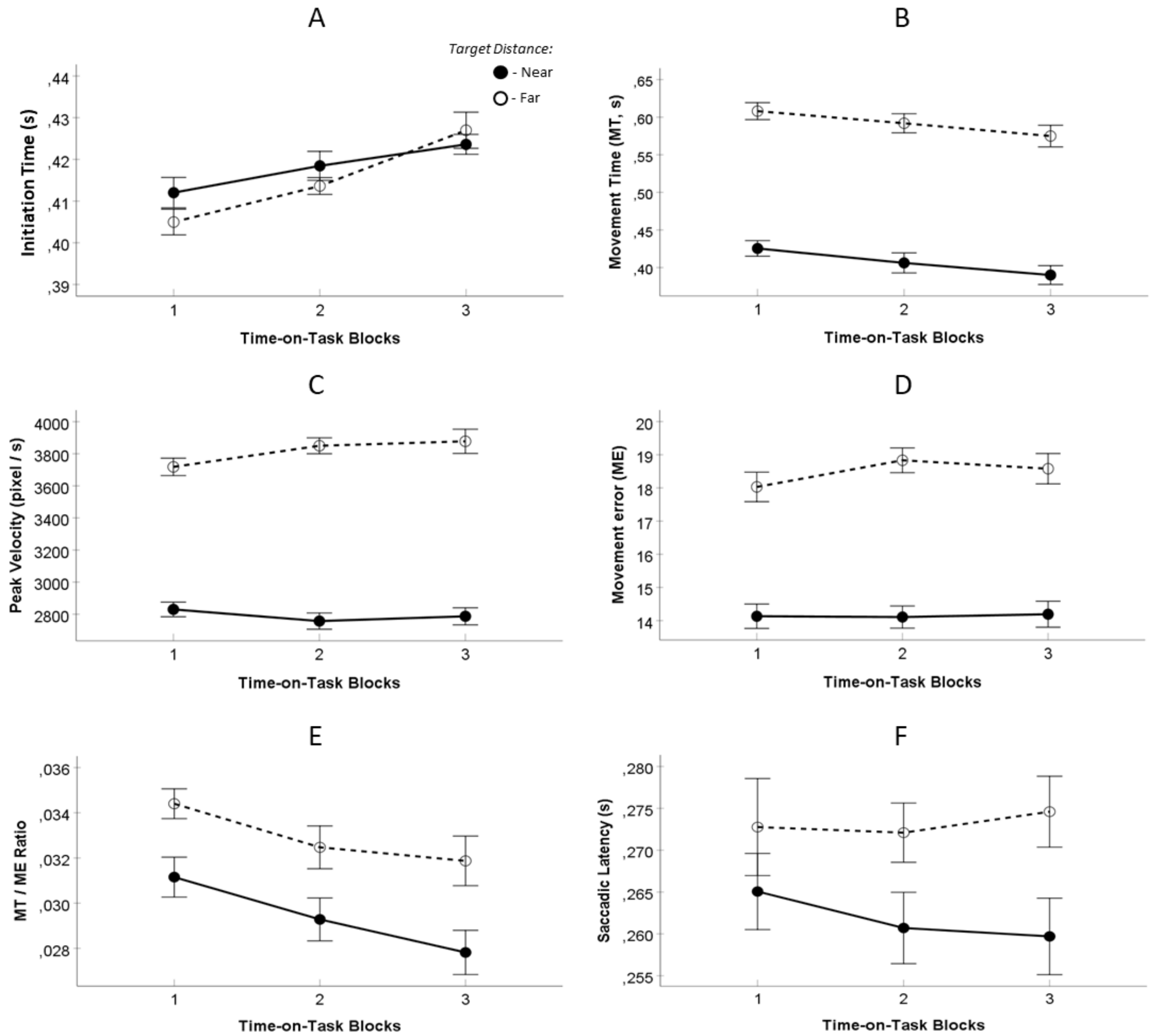

Figure 2. Results of the five pointing performance measures (A – E) and saccadic latency (F) in Experiment 1. Error bars represent within-subject error (Cousineau, 2005).

3.2. Experiment 2

3.2.1 Methods

Participants

Thirty undergraduate students participated for extra course credits. The data of five participants were excluded by applying the same exclusion criteria as in Experiment 1. The final dataset consisted of twenty-five participants (19 females, 2 left-handed, aged between 18 and 20, M = 21.44, SD = 3.12). Self-reported sleep duration had a mean of 7.92 h (SD = 0.96). The statistical power was adequate to detect significant differences (see a priori power calculation above).

Task and Stimuli

The experimental procedure and the task was identical to that of Experiment 1, except that the number of target locations was reduced to four (i.e. two positions on each side and each circle; see Figure 1B). Importantly, each target was located on the horizontal axis (y = 0), thus only horizontal movements were required to reach the target.

Data analysis

The data analyses were identical to those described in Experiment 1.

3.2.2. Results

Subjective fatigue was significantly increased by the end of the continuous performance of the task ($t(24) = -4.48$, $p < .001$). In addition, in line with the first hypothesis, and replicating the results of Experiment 1, the initialization of pointing movements became significantly slower as a function of Time-on-Task ($F(2,48) = 6.27$, $p < .01$, $\eta_p^2 = .21$). Similar to Experiment 1, saccadic latencies showed no significant change with Time-on-Task ($F(2,48) = 2.37$, n.s., $\eta_p^2 = .09$). In the movement execution phase, movement error significantly increased ($F(2,48) = 3.48$, $p < .05$, $\eta_p^2 = .13$), and movement time marginally significantly decreased with Time-on-Task ($F(2,48) = 2.97$, $p = .06$, $\eta_p^2 = .11$). In addition, we found a significantly decreasing MT/ME ratio as participants spent longer time with the task ($F(2,48) = 7.11$, $p < .01$, $\eta_p^2 = .23$). That is, the results clearly supported the second hypothesis about a more impulse movement execution under fatigue. In contrast to Experiment 1, the analysis of fixation instability yielded a significant Time-on-Task effect ($F(1,24) = 6.90$, $p < .01$, $\eta_p^2 = .22$): fixation instability linearly increased from the first to the last block of trials.

3.3. Experiment 3

3.3.1 Methods

Participants

Twenty-seven undergraduate students participated for extra course credits. Applying the same fixation criteria as before, three participants were excluded leaving a total of twenty-four participants (18 females, 3 left-handed, aged between 19 and 34, M = 23.92, SD = 4.66). Based on self-report, the mean sleep duration was 7.97 h (SD = 1.18).

Task and Stimuli

In Experiment 3, the same target positions were used as in Experiment 2 and the procedure of the experiment was also identical to those used in the first two experiments. Experiment 3, however, was different with respect to the additional trial conditions. Specifically, three auditory cue conditions were used: Orientation cue, Central cue and No cue conditions. The auditory cue was a 250 Hz tone presented for 200 ms via regular earphones. The cue-target interval was 200 ms. In the Orientation cue condition, the cue was presented monaurally to either the left or the right ear always on the side of the screen where the actual target was presented. Participants were informed that the monaural cues indicate the side of the target location. In the Central cue condition, the cue was presented binaurally, while in the No cue condition, the cue was omitted. In this experiment, the auditory signal accompanied with the visual feedback in the first two experiments was omitted in order to avoid interference with the auditory cue. To ensure balance in the number of trials across conditions, in Experiment 3, there were 72 trials in each block. Please notice that, Experiment 3 included more number of trials than Experiment 1 and 2, therefore this experiment lasted longer, until about 20 minutes.

Data analysis

The data analyses were identical to those described in Experiments 1 and 2 except that, in addition to the factors of Time-on-Task and Target-distance, the Cue (three auditory cue conditions) was also used as a within-subject factor in the rANOVA.

3.3.2 Results

Continuous performance of the task was associated with a significant increment in subjective fatigue indicating that the pointing task remains fatiguing for the participants even if it is combined with a cueing paradigm ($t(23) = -3.42$, $p < .01$). The analysis of initiation time yielded a significant main effect of Time-on-Task with a slowing trend ($F(2,46) = 4.27$, $p < .05$, η_p^2 =

.16), however, the corrected post-hoc analysis did not reach significance level when testing the differences between the three blocks of trials. There was a significant main effect of Cue with significant differences between all cue conditions ($F(2,46) = 575.93$, $p < .001$, $\eta_p^2 = .96$). Initiation time on trials following an Orientation cue was shorter compared to the other two cue conditions suggesting that the Orientation cues successfully directed participant's attention toward the possible location of the target and reduced the time required to initiate the pointing movement. The Central cues also turned out to be advantageous: initiation time on trials following a Central cue was found to be shorter than on trials without such a cue suggesting that after being presented by an auditory cue participants became generally more alert and reacted faster.

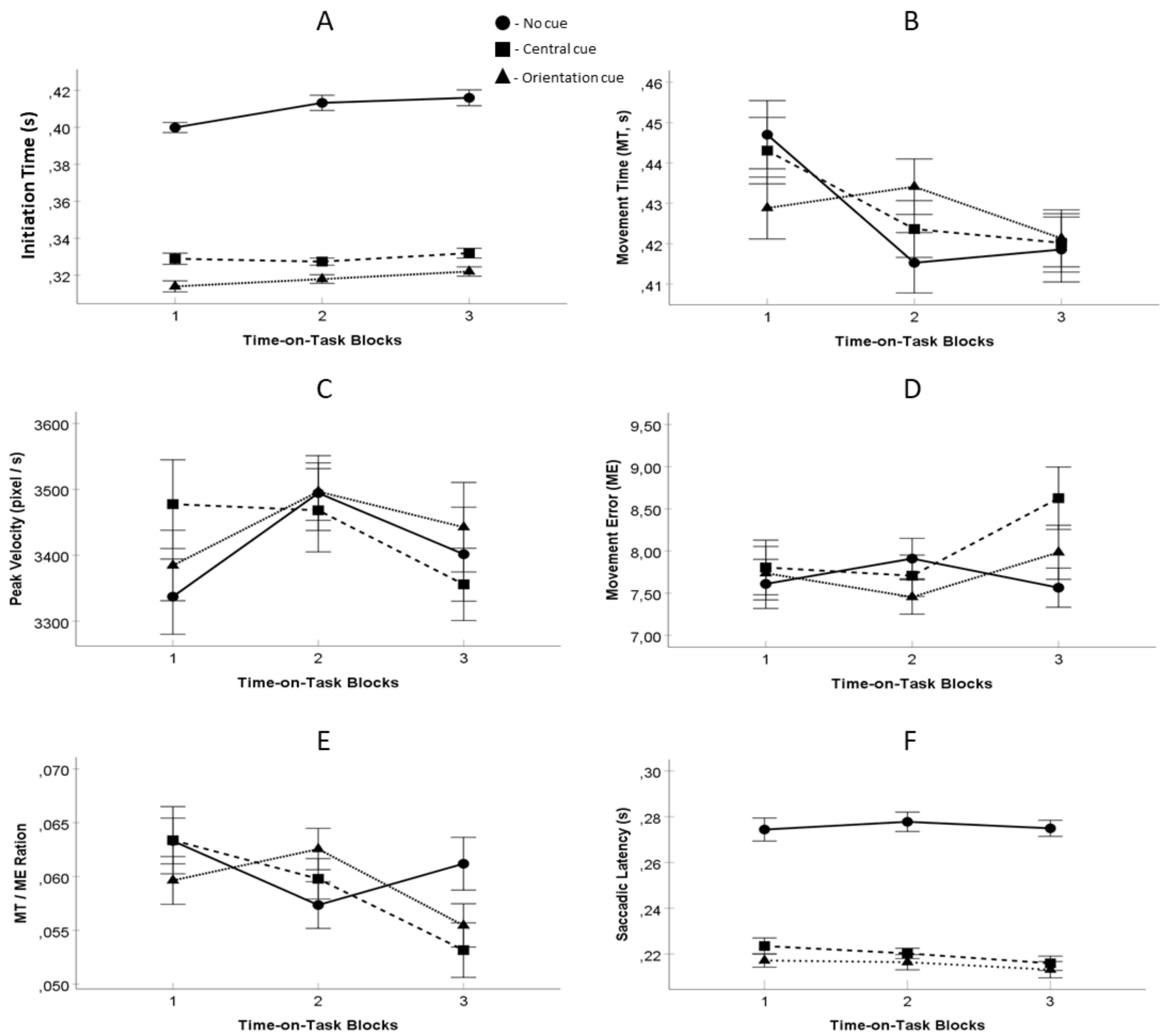

Figure 3. Results of the five pointing performance measures (A – E) and saccadic latency (F) in Experiment 3. Error bars represent within-subject error (Cousineau, 2005).

Pertinent in this study was that the Time-on-Task x Cue interaction on initiation time was also significant ($F(2,46) = 2.84$, $p < .05$, $\eta_p^2 = .11$). Follow-up analysis revealed a significant main effect of Time-on-Task for the No cue condition ($F(2,46) = 5.71$, $p < .05$, $\eta_p^2 = 0.20$) showing shorter initiation times in the first block compared to the third block of trials. In contrast, there was no significant Time-on-Task effect on trials preceded by a Central cue ($F(2,46) = 0.85$, *n.s.*, $\eta_p^2 = 0.04$) or an Orientation cue ($F(2,46) = 2.32$, *n.s.*, $\eta_p^2 = .09$). The significant advantage of Orientation and Central cues over the No cue trials was observed for saccadic latencies as well ($F(2,46) = 210.03$, $p < .001$, $\eta_p^2 = .90$). Post-hoc analyses showed that the initialization of saccadic eye movements and the response time were significantly longer when no cue preceded the target. The non-significant Block x Cue interaction ($F(2,46) = .83$, *n.s.*, $\eta_p^2 = .04$) for saccadic latencies suggest that the advantage of Orientation and Central cues over the No cue trials was unaffected by Time-on-Task. These findings suggest that participants' attentional orientation ability was not compromised as they became tired, and they remained alert for fast, phasic initiations. In addition, importantly, the results in the No cue condition replicated the finding of the first two experiments and supported our first hypothesis showing that the initialization of mouse pointing movements in the absence of auditory signals slows down with increasing Time-on-Task.

For the execution phase of the movements, we found a significant Time-on-Task x Cue interaction for MT/ME ratio ($F(2,46) = 3.22$, $p < .05$, $\eta_p^2 = .12$). As the further analysis of this interaction showed, the MT/ME decrement over time was significant only for the Central cue condition (Main effect of Time-on-Task; No cue: $F(2,46) = 1.72$, $p = .19$, $\eta_p^2 = .07$; Orientation cue: $F(2,46) = 2.83$, $p = .07$, $\eta_p^2 = .11$; Central cue: $F(2,46) = 3.38$, $p < .05$, $\eta_p^2 = .13$). This disadvantageous effect of the Central cues came mainly from the more erroneous movement execution with Time-on-Task. More specifically, the further analysis of the significant Time-on-Task x Cue interaction for movement errors ($F(2,46) = 2.47$, $p < .05$, $\eta_p^2 = .10$) revealed that, in the third block, participants' movement execution on Central cue trials became significantly more erroneous compared to No cue trials (ME: $t(23) = -3.703$, $p < .01$). In sum, these findings may suggest an alerting effect of the Central cues: this cue type may have alerted and urged participants to perform the movement response, which, however, was resulted in more erroneous movements as the participants became more fatigued.

3.4. General discussion

In three experiments, we found evidence that both the preparatory and the execution phases of pointing movements are affected by increasing Time-on-Task. More specifically, in line with our first hypothesis, the findings of all three experiments converged on the conclusion that the participants took longer to initiate their movement as they spend more time on the pointing task. In addition, our second hypothesis on movement execution also received support: faster but less precise movements were executed with increasing Time-on-Task. The findings imply that participants' tonic alertness declined and compromised the cognitive control in a top-down manner resulting in a slow initialisation and an impulsive movement execution. In contrast, our findings suggest that alternative explanations such as a fatigue-related decline in phasic alertness or deterioration in attentional orientation ability are not plausible. In Experiment 3, the comparison of No cue and Central cue conditions provided the opportunity to examine the changes in the participants' phasic alertness, however, the advantage of Central cue trials over No cue trials was found in the whole duration of the task, indicating no reduce in phasic alertness. Similarly, initiation time and saccadic latencies were faster in Orientation cue trials than in Central cue trials, and this difference remained constant over the whole duration of the task. This finding implies that allocating attention to the target remained insensitive to the detrimental effect of Time-on-Task. In line with this, the analyses of saccadic latencies showed no significant change over time in all three experiments, providing further support for the notion that participants' orientation ability remained insensitive to the effects of fatigue. Finally, the finding of Experiment 2 suggests that fatigue-related slowing in movement initiation may also occur if individuals focus their attention on a relatively small target relevant area, and can prepare their movement track more easily because of the simple horizontal positioning of the targets.

4. Time-on-Task-related changes in autonomic nervous system activity reflected by heart rate variability during prolonged task performance

4.1. Methods

Participants

Forty-four participants (under- and post-graduate students), in a medication-free health condition, with normal hearing and normal or corrected-to-normal vision participated in the study. There were 22 participants in the Gatekeeper task group and 22 participants in the Documentary-viewing group. Due to technical failures, the data of three participants were excluded from the analyses. Thus, the final dataset contained data from 20 participants (11 females, mean age: 21.2 with SD of 2.21, range: 19-27) in the Gatekeeper task group and 21 participants (11 females, mean age: 22.5 with SD of 3.9, range: 18-29) in the Documentary-viewing group. Participants in the two groups were matched in age ($t(39) = -1.33$, $p = .19$) and gender ($\chi^2 = .22$, $p = .64$). All participants provided written consent. The minimum sample size was estimated by a piori power calculation. The recommended minimum sample was 28 participants to achieve a power level of 90% at an alpha < 0.05 (by Gpower 3.1., Faul et al., 2009), thus , the final dataset of 41 participants had the appropriate statistical power to test our hypotheses.

The Gatekeeper task and Documentary film viewing

Participants in the Gatekeeper task group performed an adapted version of the Gatekeeper task from Heathcote et al. (2014, 2015) which is a dual 2-back task with visual and auditory stimuli. The Gatekeeper task has a game-like character: participants need to imagine that they are a nightclub doorperson and need to memorize the door and the password used by the guests of the club for entry. This game-like feature of the task is an asset because it is expected to enhance task engagement, which may lead to less boredom during Time-on-Task. On each trial of the Gatekeeper task, an auditory and a visual stimulus were presented simultaneously, and the participants were asked to compare the actual stimuli with the stimuli presented two trials earlier (i.e. 2-back task). The auditory stimulus was one of three spoken letters ("A", "E", or "I) presented via loudspeakers for 500 ms. The visual stimulus was an image (5.58° x 7.65°) depicting three doors positioned right next to each other and one of the doors was always highlighted with red colour. The visual stimulus was presented at the centre of the screen for 2500 ms or until response. Four different stimulus conditions were prepared. For double target condition, both the visual and auditory stimuli were identical to those presented two trials earlier. For the single target conditions, a 2-back match occurred either for the auditory stimulus (single auditory target condition) or for the visual stimulus (single visual target condition). For the no target condition, both the visual and the auditory stimuli were different to the stimuli shown two trials earlier. Participants were needed to indicate by key press whether a 2-back match (i.e. the position of the red door and/or the type of the spoken letter had a match with the stimulus attributes two trials back) occurred in any of the modalities. Prior to the task, speed and accuracy were equally emphasized. No feedback was given about the correctness of the response. The intertrial-interval was 2500 ms.

The participants in the Documentary-viewing group watched three documentary films (about 30 minutes each) for 1.5 hours: Planet Earth Episode 7 Great plains (2007); When we left Earth – The NASA missions: The Shuttle (2008); and Ocean oasis (2000) (see also a recent study by Takács et al., 2019). The films were presented in a counterbalanced order across participants. A few emotionally arousing scenes were cut from the documentaries without creating strange transitions in the narrative actions.

Self-reported measures of fatigue and workload

In each group, participants completed the NASA Task Load Inventory ($NASA_{TLX}$; Hart and Staveland, 1988). The $NASA_{TLX}$ is a multidimensional self-reported measure to assess individuals' perceived workload during the task on *6* scales with 21 gradations: mental demand; physical demand; temporal demand; overall performance level; effort; and frustration level. Participants were also asked to indicate the level of fatigue they experienced on a Visual Analogue Scale (see Study 1).

Heart rate variability measurement

ECG data were digitized at a sampling rate of 1 kHz at 16-bit resolution with a CED 1401 Micro II analogue-digital converter device (CED, Cambridge, UK). The ECG signals were visually inspected, and artefacts were corrected, and if necessary removed. Subsequently, participants' R-R intervals, in milliseconds, were extracted using Spike2 software. The time elapsed between two successive R-waves (R-R intervals) were analyzed further by Kubios HRV analysis package 2.0 (Tarvainen et al., 2014). The artefacts within the R-R intervals were again corrected using the low artefact correction option of the Kubios software: detected artefact beats were replaced using cubic spline interpolation. Frequency-domain, time-domain, and non-linear HRV measures were calculated.

The frequency indices included the absolute high frequency power (0.15 Hz - 0.4 Hz; ms^2; HF), the log-transformed high frequency power ($_{ln}$HF), the absolute low frequency power (0.04 Hz – 0.15 Hz; ms^2; LF), the log-transformed low frequency power ($_{ln}$LF) and the ratio of the power in low-, and high-frequency bands (LF/HF). The time-domain measures included the mean heart rate (HR, beats/min), the root mean square of successive differences (RMSSD, ms), the natural logarithm of RMSSD ($_{ln}$RMSSD), and the percent of the number of pairs of adjacent RR intervals differing by more than 50 ms (pNN50; %). The non-linear measures included the short-term HRV as a measure of the width of the Poincaré cloud (SD1), and the long term HRV as a measure of the length of the Poincaré cloud (SD2).

We used two different intervals for the calculation of each HRV index: 4-minute intervals; and 15-minute intervals. The 4-min intervals were the resting period before the experiment, the first 4 minutes of the first experimental block, the last 4 minutes of the fifth experimental block, the resting period during the break, and, finally, the first 4 minutes of the post-break task block. These short intervals were used in the analysis of the reactivity and recovery effects. In addition to the HRV measures, for each trial, post-response cardiac activity was also calculated as the average difference in the R-R intervals during the 2.5s-long post-response period. The larger average difference reflected a slower activity after response.

Procedure

Figure 4 schematizes the procedure of the experiment in the two groups. Participants were asked to get adequate sleep during the night prior to the experiment and to abstain from alcohol and caffeine-containing substances before the experiment. In addition, they were told that they should avoid exhausting physical and mental activities (e.g. physical workout, studying for a class) before the experiment. Participants' sleep duration was monitored using an actigraph (Gatekeeper task group: 7.46h, SD = 1.64h; Documentary-viewing group: 7.82h, SD = 1.48h) and by self-reporting (Gatekeeper task group: 7.67h, SD = 1.61); Documentary-viewing group: 7.82h, SD = 1.48). Participants in the two experiments did not significantly differ in self-reported sleep ($t(39) = 1.15$, $p = .26$) or in the actigraph data ($t(39) = - .70$, $p = .49$).

Following the sleep-related questions, the electrocardiographic (ECG) electrodes were set up (three chest electrodes, Lead II.). Then, the task was explained to the participants. Participants in the Gatekeeper group performed *72* practice trials, while those in the Documentary-viewing group had familiarization period by being shown some example scenes from the documentaries. After that, participants in both groups indicated their actual experience with fatigue on the VAS and the perceived level of cognitive load on the $NASA_{TLX}$. This was followed by a 4 minutes long resting ECG period. Then, the ToT-phase followed. During this ToT-phase, participants in the Gatekeeper group performed *5* blocks of 300 trials without rest (1500 trials in total, ~ 1.5 hours). In the Documentary-viewing group, the duration of the ToT-phase was 1.5 hours as well. When the 5 blocks of trials were completed or the documentary films ended, participants again filled in the subjective measures and they were asked to estimate the time spent with the task (in minutes). In addition, they were also asked to estimate the time they spent with the task or the films. Subsequently, participants had a break of 12 minutes. During the first 4 minutes of this break period, resting ECG was recorded. After the break, participants were asked to indicate their fatigue level again. Then, participants in the Gatekeeper group performed an additional block of 300 trials, while the Documentary-viewing group watched documentaries for another 18 minutes. At the end of this post-break block, the participants had to fill in their fatigue level and perceived load during the last block.

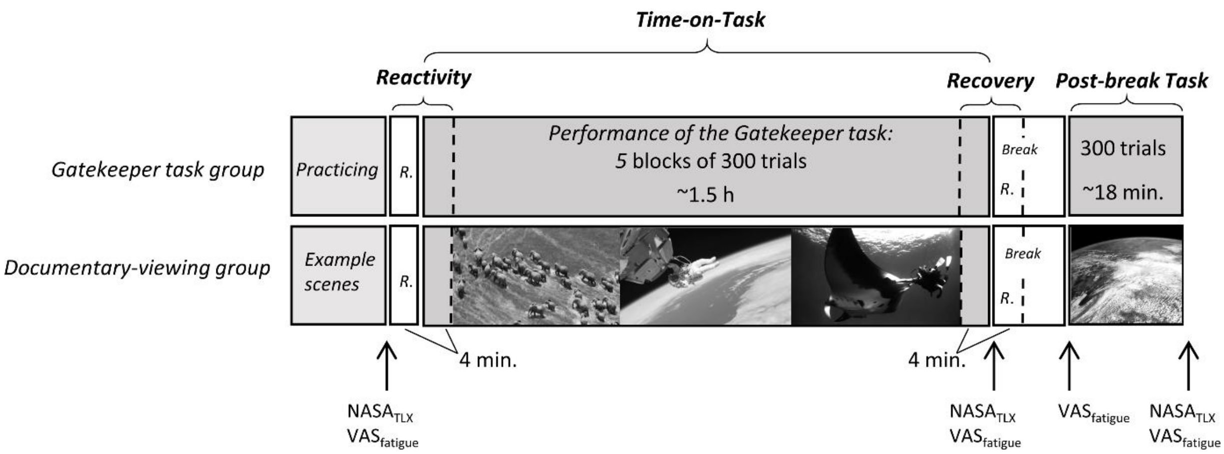

Figure 4. Schematized procedure of the study in the Gatekeeper task group and Documentary-viewing group. *R:* resting ECG recording

Data analysis

Following the guidelines of Van Breukelen (2006, 2013), we performed ANCOVAs to test the Time-on-Task effect on subjective fatigue and perceived workload: measurement after the ToT-phase was used as the dependent variable, Group (Gatekeeper vs. Documentary) as a fixed factor, and the pre-Time-on-Task measure as a covariate. The same method was used to test the effects of the post-break block on subjective measures. Similarly, the effect of the break on fatigue was tested with the post-break fatigue level as the dependent variable, Group as a fixed factor and post Time-on-Task fatigue as a covariate.

Similarly, for cardiac parameters, reactivity was tested by an ANCOVA with the first 4 minutes of the first Time-on-Task block as the dependent variable, Group as a fixed factor and pre-experiment HRV as a covariate. For recovery, the ANCOVAs included HRV measured during the break as the dependent variable, Group as a fixed factor, and the last 4 minutes of Block 5 as a covariate. The analysis of reactivity after the break compared break-HRV with the HRV during the first 4 minutes of the post-break block. For the analysis of Time-on-Task related changes in HRV, mixed ANCOVAs were performed with Block (i.e. the first to the fifth block) as a within-subject factor, Group as a between-subject factor and pre-experiment resting HRV as a covariate. In addition, in the Gatekeeper group, post-error cardiac activity was analyzed by a rANOVA with Block and Correctness of response (correct vs. incorrect) as within subject factors.

Finally, to assess the cognitive performance in the Gatekeeper task, accuracy and reaction times on correct responses were calculated for each block and target type. The two performance measures were then subjected to *r*ANOVAs with Block (5 blocks of trials) and Target types as within-subject factors. We calculated reaction time variability (=SD of RT / mean of RT) as well and analyzed with a separate rANOVA with Block as a within-subject factor. We also analyzed post-error reaction times with Block and Correctness of response (correct vs. incorrect) as within-subject factors. In addition, separate *r*ANOVAs were performed to analyze the break-related effects (changes from block 5 to the post-break block). Significant main effects and interactions were followed-up by simple effects analysis using Bonferroni corrections.

4.2. Results

The two groups did not significantly differ from each other in terms of subjective fatigue prior to the task ($t(39) = -1.51$; $p = 0.14$), however, after the ToT-phase, participants in the Gatekeeper group indicated significantly higher levels of fatigue ($F(1,38) = 11.24$, $p < .01$, $\eta_p^2 = .23$). The Gatekeeper task was also perceived mentally ($F(1,38) = 50.89$, $p < .001$, $\eta_p^2 = .57$) and physically more demanding ($F(1,38) = 31.21$, $p < .001$, $\eta_p^2 = .45$), and more frustrating ($F(1,38) = 12.87$, $p < .001$; $\eta_p^2 = .25$). In addition, we found a significant difference between the two groups in terms of estimated time spent with the task ($t(31.76) = -6.80$, $p < .001$): while participants in the Documentary viewing group underestimated the time by 8.81 minutes, participants in the Gatekeeper group underestimated it by 50.56 minutes. In the Gatekeeper group, reaction time significantly decreased from the first to the third block of trials but remained constant after that ($F(4,38) = 9.57$, $p < .001$, $\eta_p^2 = .34$). On the other hand, RT variability significantly and linearly increased with time spent on the task ($F(4,76) = 4.51$, $p < .05.$, $\eta_p^2 = .19$), indicating more attentional lapses at the end of the task. The analysis of accuracy yielded a significant Block x Target interaction (F(12.228) = 2.11; $p < .05$; $\eta_p^2 = .10$). Further analysis revealed that the accuracy significantly dropped in the Double target condition only. After the break, however, accuracy improved significantly regardless of the target condition (F(1,19) = 13.09; $p < .01$; $\eta_p^2 = .41$). Finally, the insignificant Block x Correctness of response interactions for post-error cardiac activity and post-error reaction times suggested no significant change in motivation during the performance of the Gatekeeper task.

Table 1. Results of *m*ANCOVAs and follow-up simple effects analyses for the changes in Heart Rate and HRV in Time-on-Task.

Variables	**Analysis**							
	***m*ANCOVAs**				**Simple effects analyses**			
	Block effect		Block x Group		Block effect (fatigue group)		Block effect (control group)	
	$F_{(4,152)}$	η_p^2	$F_{(4,152)}$	η_p^2	$F_{(4,35)}$	η_p^2	$F_{(4,35)}$	η_p^2
HR	4.75**	.11	16.83***	.31	25.92***	.75	2.04	.19
RMSSD	4.01*	.10	3.57*	.09	8.96***	.51	1.69	.16
$_{\ln}$RMSSD	10.75***	.22	6.34**	.14	13.16***	.60	2.52^{m}	.22
pNN50	6.61**	.15	3.56*	.09	6.70***	.43	1.52	.15
HF	2.572^{m}	.06	2.97*	.07	4.20**	.32	.45	.05
$_{\ln}$HF	11.09***	.23	5.35**	.12	11.14***	.56	2.72*	.24
LF	12.14***	.24	2.89*	.07	6.97***	.44	4.98**	.36
$_{\ln}$LF	5.61**	.13	3.75*	.09	20.92***	.71	6.85***	.44
LF/HF	.93	.02	.20	.01	.52	.06	2.00	.19
SD2	9.81***	.21	5.09**	.12	15.04***	.63	6.96***	.44

Note. *$p < .05$, **$p < .01$, ***$p < .001$, m: $p = 0.05 – 0.06$

Figure 5. depicts the results for heart rate and HRV indices. Table 1. summarizes the results of the Time-on-Task analyses. Importantly, and in line with our expectations, the further analyses of the significant Block x Group interactions indicated that only the vagally-mediated HRV indices (i.e. RMSSD, $_{\ln}$RMSSD, HF and pNN50) increased in the Gatekeeper group with increasing Time-on-Task, while remained unchanged in the Documentary-viewing group. During the reactivity periods, two cardiac parameters, heart rate and $_{\ln}$RMSSD, showed a significant and consistent change: heart rate significantly increased (reactivity: F(1,38) = 39.93; $p < .001$; $\eta_p^2 = .51$; reactivity after the break: F(1,38) = 22.99; $p < .001$; $\eta_p^2 = .38$), while $_{\ln}$RMSSD significantly decreased (reactivity: F(1,38) = 5.54; $p < .05$; $\eta_p^2 = .13$; reactivity after the break: F(1,38) = 4.32; $p < .05$; $\eta_p^2 = .10$), when participants started performing the

Gatekeeper task. For recovery, in the Gatekeeper group, the analyses showed a significant decrease in heart rate ($F(1,38) = 16.40$; $p < .001$; $\eta_p^2 = .30$) and in the LF/HF ratio ($F(1,38) = 6.59$; $p < .05$; $\eta_p^2 = .15$), and a significant increase in four vagus-mediated HRV indices (RMSSD, $_{ln}$RMSSD, $_{ln}$HF and pNN50; all Fs > 5.7, $p = .001 – .020$).

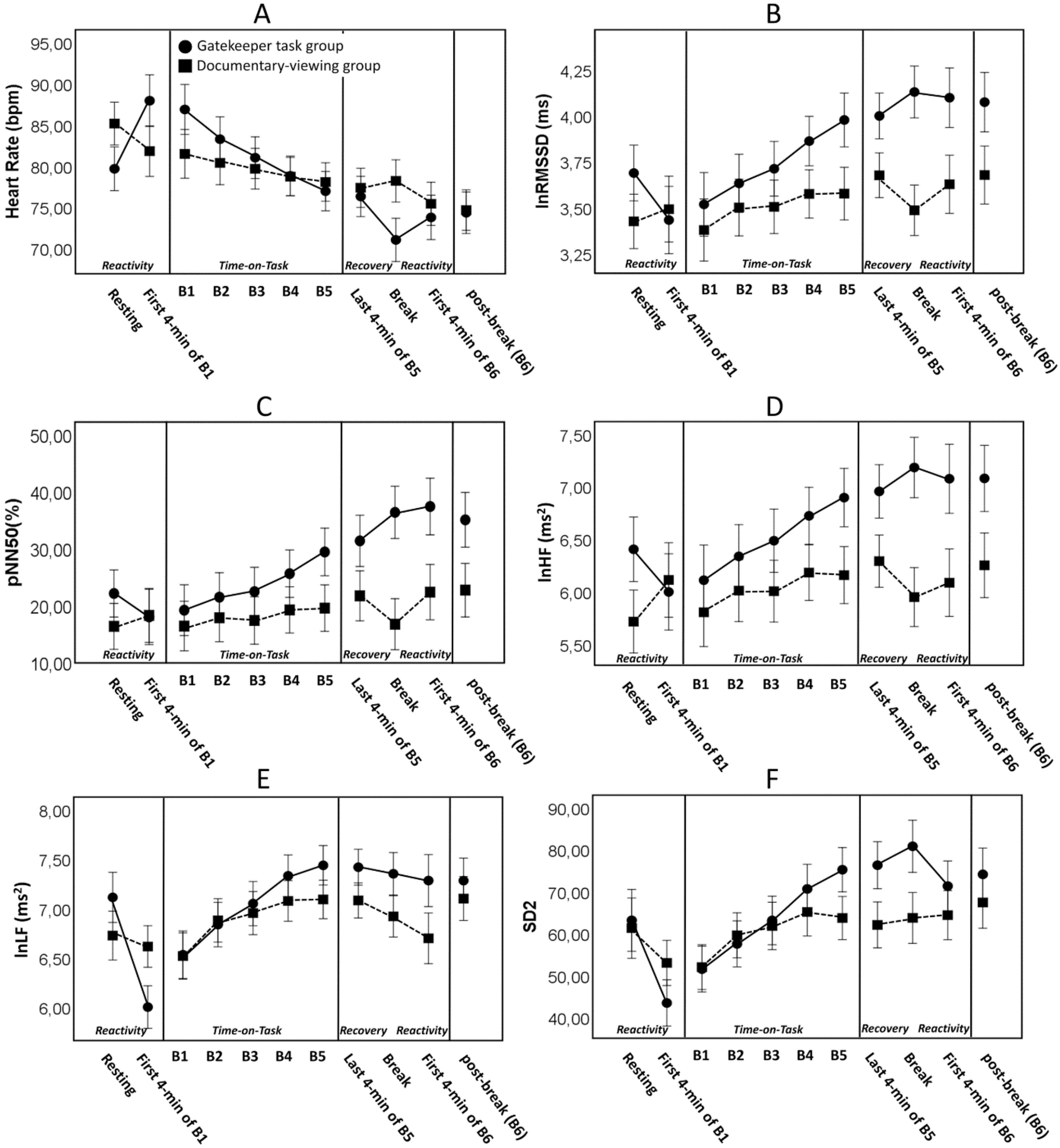

Figure 5. Results of the analyses of heart rate (A) and five HRV measures (B-F) in the Gatekeeper group (circle) and the Documentary-viewing group (square). Error bars represent the standard error of the mean.

4.3. Discussion

In the second study, we hypothesized that the vagus-mediated HRV measures show a differential trend over time in cognitively demanding and less demanding tasks. In line with our hypothesis, we found that only the vagus-mediated indices increased over time in the group that performed a bimodal working memory task, while remained unchanged in the group that watched documentary films. This finding suggest that fatigue is associated with the increased activation of the parasympathetic branch of the autonomic nervous system that serves as a relaxing system. Based on participants' post-error activity and post-error slowing, the increases in subjective fatigue and in the parasympathetic activation were not associated with motivational deficits. More specifically, participants' heart rate decelerated, and their responses slowed down after making erroneous responses suggesting that they were motivated to perfom well on the task despite the rising feeling of fatigue. Importantly, the results also indicated that many HRV indices tend to increase even during the course of a cognitively less demanding task and that some indices seem to be unaffected by the time spent on the task. These results point out the relevance of a control group or control condition in fatigue experiments investigating the HRV-fatigue associations. Furthermore, in line with the previous studies (e.g.: Helton & Russel, 2015, 2017; Lim & Kwok, 2015), we found that the cognitive performance improved after a 12 minutes long break suggesting that short breaks are sufficient for effective restoration of attentional capacities even when the cognitive task is bimodal and highly demanding.

5. The effects of fatigue on cross-modal interference in a selective attention task

5.1. Methods

Participants

Twenty-five healthy university students were enrolled in the study, however, the data of two had to be excluded due to technical issues. Thus, the final dataset of Study 3 consisted of data from 23 participants (15 female, 8 male, mean age = 21.43, SD = 1.73). Based on self-report, none of them had a history of neurological or psychiatric diseases and had normal or corrected-to-normal vision. Written consent was obtained from each of them prior to participation. Similarly to the previous two studies, a priori power analyses were conducted by Gpower 3.1. (Faul et al., 2007) to estimate the minimum sample size required to detect the effects we aimed to examine. According to these calculations, the minimum sample size to achieve a power level of 90% for alpha equal to 5% was 19. Thus, our sample size of 23 was certainly adequate for the analyses conducted.

Task and stimuli

In Study 3, we applied the modified version of the time discrimination task proposed by Lukas et al. (2014). Figure 6. depicts the schematized sequence of a trial. The task required participants to make temporal judgements about either the auditory or the visual stimulus. Prior to the simultaneous presentation of the two stimuli, the relevant modality for the actual trial was indicated by either an auditory (a 600 Hz tone presented via standard loudspeakers with a volume of 45 dB) or a visual cue (a 1.5 x 1.5 cm white cross with a visual angle of 1.25° presented at the center of the screen). The participants had to decide whether the stimulus in the cued modality was presented for a short (100 ms) or long (300 ms) duration, while they had to ignore the stimulus of the irrelevant modality. The auditory stimulus was a 400 Hz tone with a volume of 45 dB and the visual stimulus was a centrally presented white diamond (1.5 x 1.5 cm) with a visual angle of 1.25°. A response was required within a time-window of 2500ms after stimulus presentation. The response-cue interval was 1500 ms. On *congruent* trials, the duration of the visual stimulus was identical to the auditory stimulus, while, on *incongruent* trials, they differed (e.g. short visual vs. long auditory stimulus). The trials were also categorized into *modality-repetition* and *modality-switch* trials. On *modality-repetition* trials, the cued modality in the actual trial was the same as the cued modality in the previous trial, while, on *modality-switch* trials, they were not the same (i.e. auditory trial followed by a visual trial or visual trial followed by an auditory trial). The number of consecutive repetition trials varied between 2 and 5. Prior to the task, the importance of both the accuracy and speed were equally emphasized.

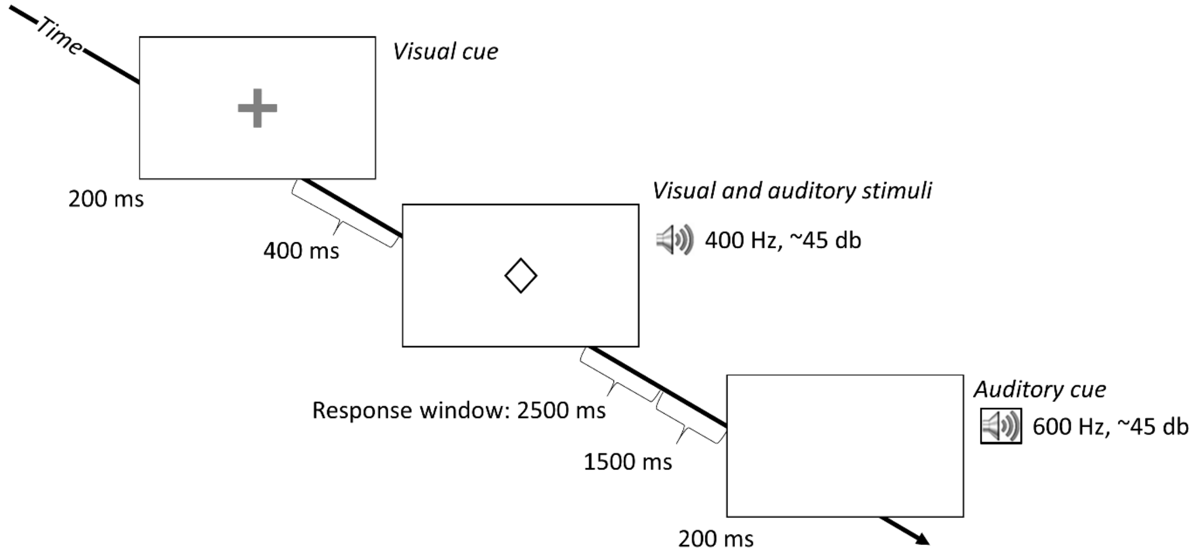

Figure 6. Schematic representation of the time discrimination task

Subjective measures

To assess participants' experience with subjective fatigue and the perceived cognitive load, the same methods were used as in Study 2 (i.e. the VAS and $NASA_{TLX}$ measures, respectively). In addition, we asked participants to rate how motivated they feel to do the task on a 7-points Likert-scale (1 referred to "*Not motivated at all*", and 7 referred to "*Very highly motivated*").

Heart rate variability

The procedure of physiological recording and the preprocessing and analysis of ECG signals were identical to that of Study 2. The pre-task resting period lasted 5 minutes. After the ToT-phase (see below), the 12 minutes long break was divided into two 5 minutes sessions, and the first 5 minutes of the break and the last 5 minutes of the break were analyzed separately. Statistical analyses were only conducted with those vagus-mediated HRV measures that were found most adequate (i.e. the ones that showed the highest effect sizes in the Gatekeeper group) in Study 2. Thus, the two indices included in the statistical analyses were $_{ln}$RMSSD and $_{ln}$HF.

Procedure

The general procedure was largely similar to that of Study 2. During the night prior to the experiment, participants wore actiwatches. Based on the actigraph measurement, the average sleep duration was 7.92 hours (SD = 1.57), while it was 7.89 hours (SD = 1.31) according to self-report. The experimental sessions started either at 10:00 or at 14:00. To determine the chronotype of the participants, the Hungarian version of the Morningness-Eveningness Questionnaire (Self-Assessment version, Terman, 2005) was administered. To avoid a large mismatch between participants' general daytime activity and the time of the experiment, participants who scored 41 or less (i.e. evening types) were only tested in the afternoon session.

After the task was explained, participants practiced the temporal discrimination task. This practice session consisted of single auditory, single visual and bimodal sessions as well. Then, the $NASA_{TLX}$ was administered and they were asked to indicate their actual level of subjective fatigue on the VAS. This was followed by the 5 minutes long resting ECG period.

At the beginning of the ToT-phase, participants were asked to answer the motivation-related question. The median rating was 6 (mean = 5.52, range = 3) indicating high levels of task-related motivation. During the ToT-phase, participants performed 5 blocks of 400 trials without break (i.e. 2000 trials in total). Within each block, the number of trials per condition was balanced (50 trials each). Stimuli were presented in pseudo-random order. The whole duration of the ToT-phase depended on reaction time as well, and thus, varied between the participants (mean = 1.55 hours, SD = 0.1). At the end of the task, participants completed the $NASA_{TLX}$ and the VAS for the third time. In addition, they were asked to estimate the time spent with the task.

The ToT-phase was followed by a 12 minutes long break. In the first and the last 5 minutes of the break, resting ECG was recorded. At the end of the break, participants were asked again to indicate their actual level of fatigue on the VAS. Then, the motivation-related question was asked for the second time. This time, the median rating was 3 (mean = 3.43, range = 6) suggesting a drop in the level of motivation compared to its level prior to the ToT-phase. After that, participants performed the task for an additional block of 400 trials. This post-break block lasted approximately 18 minutes. All task parameters remained the same as before. Finally, after the post-break block, participants reported their level of fatigue as well as the perceived workload on the VAS and the $NASA_{TLX}$, respectively.

Data analysis

To analyze the changes in subjective fatigue, an rANOVA was conducted with Administration time (i.e. the 4 administrations of VAS) as within-subject factor. Changes in perceived workload were analyzed by an rANOVA with two factors: Administration time (i.e. the 3 administrations of $NASA_{TLX}$) and Scale (i.e. the six scales of $NASA_{TLX}$). The estimated time spent with the temporal discrimination task during the ToT-phase was analyzed by a paired samples t-test comparing the estimated time to the actual time spent with the task.

For the cognitive performance, accuracy and reaction time on correct trials were calculated for each block and each condition. In addition, we also calculated the linear integrated speed accuracy score (LISAS) proposed by Vandierendonck (2017) according to the following formula:

$$LISAS = RT + SD_{RT}/SD_{ER} \times ER,$$

where RT refers to the mean reaction time, SD_{RT} refers to the standard deviation of reaction time, ER is the mean error rate and SD_{ER} is the standard deviation of the error rate. The performance measures were separately entered into 2x2x2x5 rANOVAs with Modality (auditory vs visual), Modality-switching (modality-repetition vs. modality-switch), Congruence (congruent vs. incongruent) and Block (5 block of trials in the ToT-phase) as within-subject factors. The effects of break on cognitive performance were analyzed by a similar rANOVA except that the Block factor had only 2 levels (the fifth block of the Time-on-Task period vs. the post-break block).

The analyses of cardiac parameters were similar to that of Study 2. Reactivity-, and recovery-related changes were analyzed by paired samples t-tests. For *reactivity*, we compared the first 5 minutes of the first block to the resting ECG recording prior to the ToT-phase. For *recovery*, we compared the first 5 minutes of the break to the last 5 minutes of the ToT-phase. For *reactivity after the break*, the first 5 minutes of the post-break block was compared to the last 5 minutes of the break. Finally, Time-on-Task-related changes in heart rate and HRV were analyzed by rANOVA with Block (i.e. the 5 block of trials) as a within-subject factor.

5.2. Results

The rANOVA performed on VAS ratings yielded a significant Administration time main effect ($F(3, 66) = 23.82$, $p < .001$, $\eta_p^2 = .52$). The post-hoc analysis indicated that subjective fatigue was significantly higher at the end of the ToT-phase than before and that the level of fatigue decreased at the end of the break. For the cognitive workload assessed by $NASA_{TLX}$, the analyses revealed significant Administration time ($F(2, 44) = 21.09$, $p < .001$, $\eta_p^2 = .49$) and Scale ($F(5, 110) = 21.04$, $p < .001$, $\eta_p^2 = .49$) main effects, and their interaction was also found to be significant ($F(10, 220) = 4.97$, $p < .001$, $\eta_p^2 = .18$). Further analyses showed that all aspects of cognitive workload increased during the ToT-phase, except for temporal demand ($p = .25$).

Similarly to Study 2, participants significantly underestimated the time spent with the task (t(22) = -8.45, $p < .001$).

Table 2. Results of the analysis of cognitive performance measures in the ToT period

Main effects and interactions		**Accuracy**		**Reaction time**		**LISAS**	
	df	F	η_p^2	F	η_p^2	F	η_p^2
Block (5 blocks of trials)	4,88	6.05**	.22	11.68***	.35	8.79***	.28
Modality (visual vs. auditory	1,22	26.33***	.54	4.54*	.17	.94	.04
Modality-switch (repetition vs. switch)	1,22	26.39***	.54	92.41***	.81	83.24***	.79
Congruence (congruent vs. incongruent)	1,22	75.95***	.77	56.30***	.72	6.54***	.73
Modality x Modality-switch	1,22	.01	.00	36.39	.62	22.92***	.51
Modality x Congruence	1,22	27.10***	.55	8.22	.27	12.92**	.37
Modality-switch x Congruence	1,22	6.84*	.24	11.19**	.34	34.19***	.61
Modality x Modality-switch x Congruence	1,22	.87	.04	1.15	.05	.37	.02
Block x Modality	4,88	.87	.04	5.36**	.20	3.18*	.13
Block x Modality-switch	4,88	.26	.01	6.34**	.22	4.63**	.17
Block x Congruence	4,88	1.32	.06	2.68^{m}	.11	2.32^{m}	.10
Block x Modality x Modality-switch	4,88	.32	.01	5.44**	.20	5.36**	.20
Block x Modality x Congruence	4,88	.34	.01	1.68	.07	3.86*	.15
Block x Modality-switch x Congruence	4,88	2.10	.09	.12	.00	1.04	.04
Block x Modality x Modality-switch x Congruence	4,88	1.93	.08	.52	.02	.39	.02

*p < .05, ***p* < .01, ****p* < .001

Results of the analysis of cognitive performance are summarized in Table 2. Importantly, in line with our hypothesis, the analysis of LISAS revealed a significant Block x Modality two-way interaction and a significant Block x Modality x Congruence three-way interaction (see Figure 7.). We found that the performance on visual trials significantly declined from the third to the fifth block of trials, while the performance on auditory trials remained unchanged. This suggest that the temporal discrimination of visual stimuli was more sensitive to the detrimental effects of fatigue. In addition, the further analysis of the Block x Modality x Congruence interaction showed that the congruency effect (i.e. the interfering effect of incongruent irrelevant stimuli) in visual trials increased with Time-on-Task. More specifically, we found a significant Block main effect ($F(4, 88) = 5.20$, $p < .01$, $\eta_p^2 = .19$) for incongruent visual trials and the post-hoc analyses revealed that the performance on these trials increased from the first to the third block ($t(22) = 3.66$, $p < .01$), but significantly declined from the third to the fifth block ($t(22) = -3.99$, $p < .01$). In contrast, there were no significant increases in LISAS (i.e. declining performance) for congruent visual trials, congruent auditory trials and incongruent auditory trials. After the break, however, the LISAS on congruent auditory trials significantly decreased (Block x Modality x Congruence: $F(4, 88) = 7.29$, $p < .05$, $\eta_p^2 = .25$; Block x Congruence on auditory trials: $F(1, 22) = 8.46$, $p < .01$, $\eta_p^2 = .28$; block 5 vs. post-break block: $t(22) = 2.40$, $p < .05$), suggesting that the break had positive effects only on the modality considered to be preferred in temporal tasks.

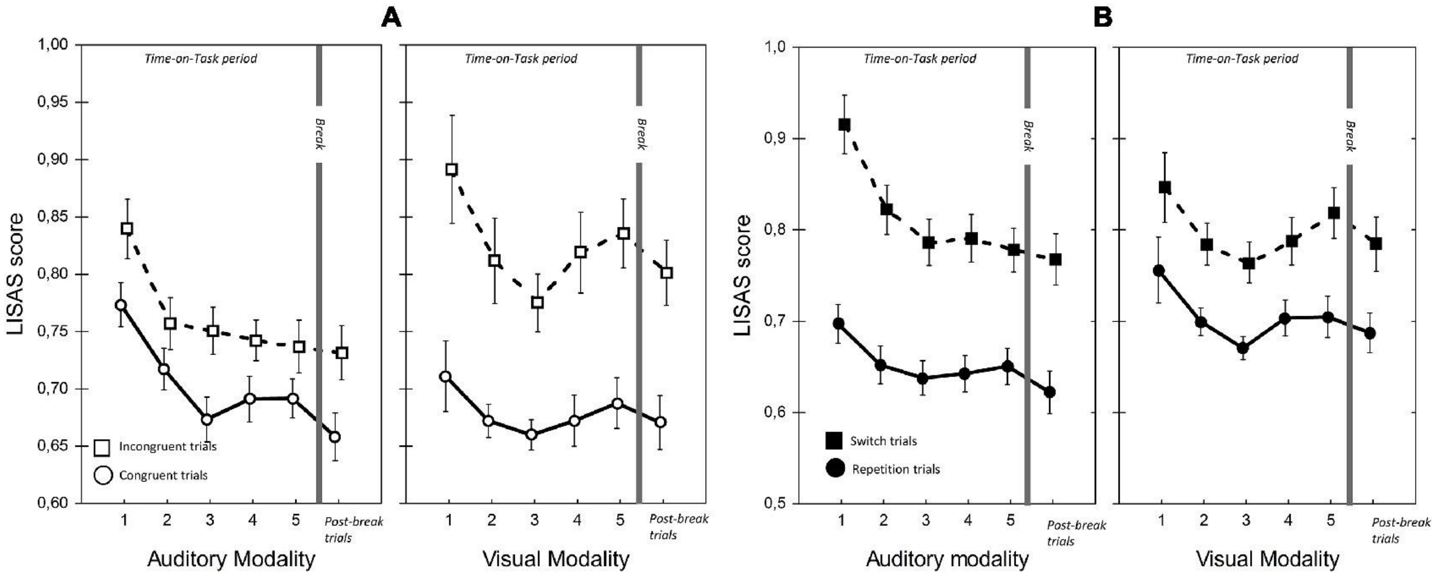

Figure 7. Results of LISAS scores for visual and auditory modalities in the two Congruence (A) and Modality-switch conditions (B). Error bars represent within-subject error (Cousineau, 2005).

Heart rate showed a significant linear decrease over time during the ToT-phase ($F(4,88) = 13.66$, $p < .001$, $\eta_p^2 = .38$). In the post-break block, heart rate was significantly lower than in the last 5 minutes of the break ($t(22) = 2.59$, $p < .05$). The analyses of the two vagally-mediated HRV indices in the Time-on-Task period yielded significant Block main effects ($F(4,88) = 6.20$, $p < .01$, $\eta_p^2 = .22$; $_{\ln}$HF: $F(4,88) = 3.61$, $p < .05$, $\eta_p^2 = .14$). Both measures increased linearly with increasing time spent with the task.

5.3. Discussion

Our aim was to investigate the effects of fatigue on the auditory and visual temporal processing, as well as cross-modal conflicts. According to the modality appropriateness hypothesis (Welch and Warren, 1980), in temporal tasks, the auditory modality dominates the task due to its greater temporal resolution. Therefore, we expected that temporal discrimination based on auditory stimuli will be robust against the effects of fatigue, while the temporal discrimination of visual stimuli will decline over time. Our results confirmed this hypothesis, because we found that performance on visual trials indeed decreased after approximately 45 minutes but the performance on auditory trials remained constant. In addition, it has been shown that the interference of auditory distractors on visual processing increased over time, however, the interference of visual distractors on auditory processing did not change with increasing time spent with the task. These are in line with the Compensatory Control Model (Hockey, 1997, 2011) of fatigue suggesting that fatigued individuals make strategic adjustments in order to maintain task performance, for example, by allocating more resources to the primary aspect of the task (i.e. the dominant auditory stimuli) at the expense of the secondary aspect (i.e. the visual stimuli). With other words, as a result of being fatigued, participants disengaged and attended less to the visual stimuli and focused more on the auditory stimuli, because the auditory modality is more appropriate for temporal discrimination.

Importantly, in line with the results of Study 2, we also found further evidence for an enhanced parasympathetic activation under fatigue indicated by decreasing heart rate and increasing vagally-mediated HRV. These finding thus provide further support for the notion that HRV is a reliable biomarker of fatigue and could potentially be used for the effective detection and estimation of fatigue.

6. Predicting and detecting mental fatigue using machine-learning algorithms trained on HRV data

6.1. Methods

Dataset

For the analysis, we combined the datasets of three mental fatigue experiments. A subset of the dataset consisted of the data already presented in the dissertation: data of the Gatekeeper group (n = 20) from Study 2 and data of Study 3 (n = 23). To ensure an appropriate sample size, additional data were collected for Study 3 (n = 15; i.e.: for 38 participants, fatigue was induced by the time discrimination task) and the data of a third fatigue experiment that used a bimodal Stroop task to induce fatigue was also included (n = 27). Thus, the final dataset consisted of the data of 85 individuals.

Bimodal Stroop task

The task used in the third experiment (n = 27) was a bimodal semantic Stroop task with auditory and visual stimuli presented simultaneously. Two modality conditions were introduced. In the auditory condition, participants had to attend the auditory stimulus and ignore the visual stimulus, while in the visual condition, they had to attend the visual stimulus and ignore the auditory one. The modality condition changed after every 12 consecutive trials. The auditory (presented via loudspeakers at an intensity of approx.. 45 dB) and the visual stimuli (white letters on grey background) were spoken and written names of animals (birds and mammals), respectively, presented for 700 ms. Participants were asked to decide whether the attended written or spoken name of the animal presented in the actual trial referred to a bird or a mammal. Participants responded in a time window of 1500 ms by pressing one key on the response box for birds or another key for mammals. The intertrial-interval varied between 500 and 3000 ms. This semantic Stroop task consisted of 3 blocks of 432 trials (i.e. a total of 1296 trials) and lasted approx. 1.2 hours. During the whole course of the experiment, ECG was recorded with the same procedure as described in the previous chapters. The resting ECG periods before and after task performance lasted 5 minutes.

Similarly to the previous experiments, participants were asked to fill in the $NASA_{TLX}$ and to indicate their actual experience with fatigue on the VAS prior to task performance and after task completion. The analysis of ratings on the VAS revealed that the continuous performance of the semantic Stroop task significantly enhanced participants' feelings of fatigue $t(26) = 7.81$, $p < .001$). In addition, the analysis of $NASA_{TLX}$ showed that all aspects of cognitive workload (except for Time demand) increased significantly after the task (Mental demand: t(26) = 8.45, $p < .001$; Physical demand: t(26) = 6.37, $p < .001$; Performance: t(26) = 3.28, $p < .01$; Effort: t(26) = 5.68, $p < .001$; Frustration: t(26) = 4.58, $p < .001$). In sum, the semantic Stroop task successfully evoked the feeling of fatigue and enhanced the perceived level of cognitive workload.

HRV measures

In each of the three experiments, HRV was calculated for four 4-minutes intervals: for the resting ECG intervals prior to the prolonged task performance and after task performance, and for the first and last 4 minutes of the task performance. The number of calculated HRV indices was remarkably higher than in the previous chapter in order to increase the predictive power of the machine-learning models (12 indices from the time domain, 16 indices from the frequency domain and 5 indices derived from non-linear analyses). However, in order to avoid overfitting, feature selection was performed prior to the training of the models (see details below).

Classification algorithms (detecting fatigue)

All programming was implemented in Python using the scikit-learn package (Pedregosa et al., 2011). The aim of the classification was to develop a set of models that are able to correctly distinguish between fatigue and non-fatigue states (i.e. are able to detect the fatigue state). Based on the source of data, the following two classification problems were addressed separately: the models were either trained on resting HRV data or task-related HRV data. For the first classification problem, the pre-task resting ECG interval was labelled as the "Non-fatigue" state and the post-task resting ECG interval was labelled as the "Fatigue" state. For the second classification problem, the first 5 minutes of the task performance was labelled as the "Non-fatigue" state, while the last 5 minutes of the task performance was labelled as the "Fatigue" state. Fatigue was operationalized as an increase in subjective fatigue (measured by VAS). Hence, the data of participants that did not have a higher post-task fatigue score than before were excluded. Thus, for the classification problems, the sample size reduced to 82, however, for each person, HRV was calculated for two intervals (fatigue and non-fatigue). Consequently, the final dataset consisted of 164 datapoints for each variable.

To avoid overfitting and to save computational time, feature selection was performed in three steps. First, by applying one of the most widely used procedures (Abraham et al., 2014), for each feature (or variable), an F-score was computed based on ANOVA. Second, for highly correlated features (i.e. a Person's r-value greater than 0.8), one of them was removed (the one with the lower F-score). Third, the mean F-score was calculated and features with F-scores lower than the mean were removed. Feature selection was performed for the two classification problems separately. For the models trained on resting HRV data, the selected features included the minimum heart rate, $_{ln}$VLF, SD2, triangular index and HF. For the models trained on task-related HRV data, the selected features included the $_{ln}$VLF, $_{ln}$LF, minimum heart rate, VLF (%), SDHR and approximate entropy.

Following feature selection, the dataset was split into a training set (70%) and a test set (30%). Four classification algorithms were used to build models and that are able to detect fatigue: support vector machine (SVM), K-nearest neighbors (KNN), logistic regression with L2 regularization and decision tree. The first three algorithms were selected to allow the comparison with previous results obtained from the same algorithms (Laurent et al., 2013; Huang et al., 2018). In addition, decision tree was selected to explore the predictive power of an algorithm that have not been used to detect fatigue before. Prior to the training, the data were standardized by z-transformation (except for the training of decision trees). Hyperparameters for each classifier were optimized through grid search with stratified 5-fold cross-validation. The hyperparameter space of the SVMs consisted of linear and radial basis function for kernel, the set $\{10^0, 10^1, 10^2\}$ for C and the set $\{10^0, 10^{-1}, 10^{-2}\}$ for γ. For KNN, k values from 1 to 20 were examined to identify the most optimal one. For the decision tree, the optimized parameter was the maximum depth (ranging from 1 to 10) of the tree. Finally, for logistic regression models, the strength of the regularization (ranging from 10^{-4} to 10^4) was optimized. Both the internal validation of the models and the evaluation of the classification performance on the testing data set (i.e. fatigue detection on unseen holdout data) were done using the area under the receiver operating characteristic curve (area under the curve, AUC). In addition, accuracy (i.e. the proportion of correctly classified cases) was also calculated to evaluate the performance of the models on the testing data set.

To test whether the fatigue detection performances of the models are higher than the chance level, permutation tests with 1000 iterations were carried out. On each iteration, a model was trained on the training data set with shuffled class labels (i.e. predictors and class labels were mismatched) and an AUC score was calculated based on the performance of the model on the (unshuffled) testing data set. We thus generated the null-distribution of AUC scores and determined whether the actual performance of the models was greater than 95% of the AUC scores obtained on shuffled data.

Regression models (predicting the severity of fatigue)

Similarly to the classification problems, regression modelling was carried out in Python with the scikit-learn package (Pedregosa et al., 2014). In the regression models, the outcome measure was the change in subjective fatigue caused by prolonged performance (i.e. the difference between the initial and the post-task rating on the VAS). Prior to training, feature selection was performed to find the best predictors. Potential predictor variables included pre-task resting HRV measures and other variables such as gender, self-reported sleep duration, initial level of subjective fatigue, type of task (i.e. Gatekeeper task, time discrimination task or semantic Stroop task) and task duration (in minutes). Due to the high correlation between HRV measures, we used the least absolute shrinkage and selection operator (lasso) method to select the most important features. The lasso regression method is known to be effective even when multicollinearity exist among the variables (Tibshirani, 1996). The following predictors were selected for model development (listed in rank-order according to variable importance): SD2 (.70), initial level of subjective fatigue (.37), RMSSD (.28) and task duration (.22).

To our knowledge, no previous studies have attempted to predict the change in subjective fatigue based on HRV data with machine-learning algorithms. Thus, we applied some of the most widely-used methods such as lasso regression, elastic net regression and random forest regression (see e.g. Elhai, Yang, Rozgonjuk & Montag, 2020; Christ, Elhai, Forbes, Gratz & Tull, 2021). The data set was first split into a training set (80%) and a testing set (20%). Hyperparameters were tuned on the training set with 5-fold cross-validation. For the lasso and elastic net regression models, the hyperparameter alpha was tuned and for the random forest regression, maximum tree depth was tuned.

Following the optimization of the parameters, the models were used to predict the change in subjective fatigue in the previously unseen testing data set. To evaluate the performance of the models, several metrics were calculated including the mean squared error (MSE), the root mean squared error (RMSE) and the R^2. In addition, the Pearson correlation coefficients between predictions and true values were calculated. Similarly to the classification problems, permutation tests with 1000 iterations were carried out to assess the significance of the R^2 values. On each iteration, the model was trained on the shuffled training data set (i.e. where the predictors and the outcome variable did not match) and the change in subjective fatigue was predicted in the (unshuffled) testing set. From the observed R^2 values, we generated the null-distribution of R^2s and determined whether the actual R^2 was greater than 95% of the R^2s trained on shuffled data.

6.2. Results

The performances of the classification models trained on resting or task-related HRV data are presented in Table 3. The evaluation metrics presented in the table and in the text refer to the models tested in the previously unseen testing sample. The best performance was achieved by SVM with radial basis function ($C = 10^0$, $\gamma = 10^{-2}$) trained on task-related HRV data (see also Figure 8.). Permutation tests demonstrated that the classification accuracy of the SVM, KNN ($k = 18$) and decision tree (maximum depth = 2) models significantly differed from the permuted null-distribution. On the other hand, the classification models trained on resting HRV data showed lower classification accuracies and did not differ significantly from the permuted null-distribution.

Table 3. Performance of the classification models on the test sample (n=50)

Classification models	**Evaluation metrics**		
	AUC	Accuracy	p
Task-related HRV			
Decision tree	.72	70%	.04
KNN (k=18)	.73	72%	.02
Logistic regression	.71	70%	.07
SVM	.75	74%	.03
Resting HRV			
Decision tree	.65	62%	.14
KNN (k=18)	.68	66%	.05
Logistic regression	.65	62%	.12
SVM	.68	70%	.05

Note. AUC: area under the curve; KNN: k-nearest neighbors; SVM: support vector machine; p: permutation test-based p value (n = 1000)

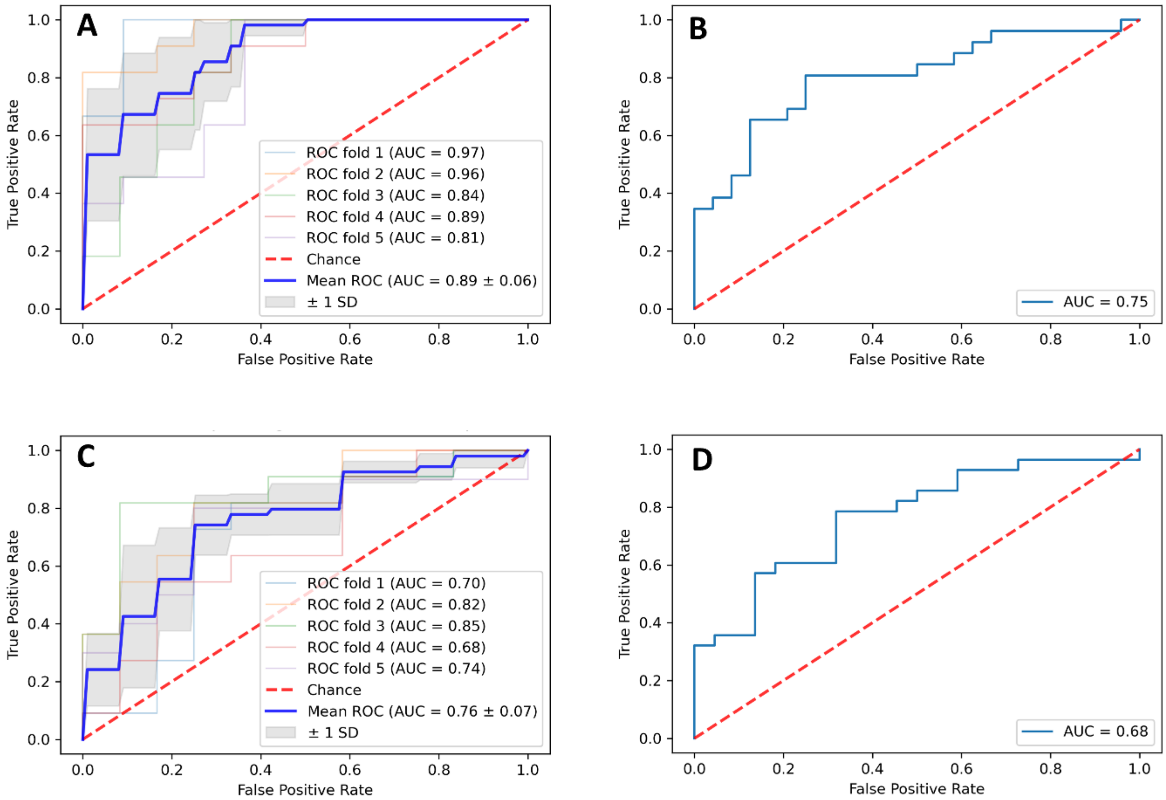

Figure 8. Training and testing of SVM algorithms on task-related and resting HRV data. (A) Training of the SVM algorithm on task-related HRV data; (B) Testing the model on the previously unseen testing data set (task-related HRV); (C) Training of the SVM algorithm on resting HRV data; (D) Testing the model on the previously unseen testing data set (resting HRV).

The results of the regression models are presented in Table 4. The models were evaluated based on their performance in the testing sample. Two models, the elastic net regression and the lasso regression model, could effectively predict the change in subjective fatigue in the testing sample. The best performance was achieved by the elastic net regression (alpha = .002). The predictions made by the model and the true values were found to be moderately correlated (r = .495). The lasso regression model was also significant according to the permutation test and the values predicted by the lasso model and the true values showed a moderate correlation (r = .490). On the other hand, the predictive power of the random forest regression model did not significantly differ from the permuted null-distribution.

Table 4. Performance of the regression models on the test sample

Regression models	**Evaluation metrics**			
	R^2	*MSE*	*RMSE*	*p*
Elastic net	.21	255.90	16.00	.01
Lasso	.19	261.92	16.18	.02
Random forest	.03	256.44	16.01	.34

Note. MSE: mean squared error; RMSE: root mean square error; p: permutation test-based p value (n = 1000)

6.3. Discussion

Consistently with previous studies, the supervised machine-learning algorithms were shown to effectively detect fatigue based on task-related HRV. However, our study's methodology offers some unique contributions to the literature. First, our sample size was relatively large compared to the previous investigations and fatigue was induced by different cognitive tasks that required different mental operations. Thus, the external validity of our results is probably higher and therefore, the models could potentially perform at a similar level even under different conditions. And second, we found that the algorithms perform better if trained on task-related HRV data compared to resting HRV. This result has both methodological and practical implications. In addition, two of the regression models with predictors such as two resting HRV indices (SD2 and RMSSD), the initial level of subjective fatigue and the duration of the task could effectively predict the change in subjective fatigue evoked by prolonged task performance.

7. Summary of the results of studies included in the thesis

The aim of the first study was to test the effects of fatigue on the preparatory and execution phases of visually-guided pointing movements in a sustained attention task. In accordance with our expectations, initiation time, a measure of the preparatory phase, significantly increased with Time-on-Task in all three experiments. We suggest that this increasing trend could not be explained by a fatigue-related deterioration in attentional orientation ability because empirical evidence seems to contradict this claim. First, saccadic latencies were not affected by Time-on-Task in either of the experiments, indicating that participants had no difficulties with orienting their attention toward the target. Second, the results of Experiment 2 showed that the fatigue-related increase in initiation time may also occur if individuals focus their attention on a relatively small target relevant area, and can prepare their movement track more easily because of the simple horizontal positioning of the targets. Finally, in Experiment 3, we found that initiation time was affected by Time-on-Task in the No cue condition but not in the Central cue or the Orientation cue conditions. These findings imply that participants' phasic alertness and orientation ability were both insensitive to the effects of fatigue. In addition, these findings also suggest that instead of the reduced level phasic alertness, the fatigue-related increase is initiation time could be rather explained by a decreased level of tonic alertness. This explanation is supported by previous studies as well showing that the prolonged performance of sustained attention tasks is linked to a depressed level of tonic alertness (Oken et al., 2006; Cose & Kleinschmidt, 2016). Regarding the execution phase of movements, the results suggest that participants became more impulsive over time as indicated by faster by more erroneous movements. These results can be explained in the context of the Compensatory Control Model of fatigue (Hockey, 1997, 2011). Particularly, in line with the predictions of the model, one aspect of the task goal (speed) was probably prioritized over another aspect of the task goal (accuracy) as a result of fatigue. Furthermore, in Experiment 3, we found that movement error was the highest for the Central cue condition by the end of the ToT-phase suggesting that auditory warning cues do not necessarily lead to better performance when the operator is fatigued.

In the second study, the main focus was on the fatigue-related changes in the activity of the autonomic nervous system. In line with our hypothesis, the activation of parasympathetic branch of the autonomic nervous system reflected the vagally-mediated HRV indices increased over time during a bimodal working memory task, while during documentary viewing, no change in the parasympathetic activity was found. These findings point out the importance of control conditions in fatigue experiments and suggest that the vagally-mediated HRV indices are reliable biomarkers of fatigue. The increased parasympathetic activity measured under fatigue was, however, not associated with motivational deficits because the analysis of post-error cardiac activity and post-error slowing in reaction time showed that participants adjusted their behaviour following errors even when they were experiencing fatigue. In line with the lack of motivational deficit, we did not find strong evidence for a decline in cognitive performance. In addition, no evidence was found for the notion that fatigue has differential effects on visual and auditory working memory processes. On the other hand, the cognitive performance in both modalities improved after a 12-minute break suggesting that well-known positive impact of rest breaks on cognitive performance can also be observed in tasks that require participants to divide their attention between two modalities.

In the third study, we hypothesized that duration judgments of visual stimuli compared to auditory stimuli will be more sensitive to the effects of fatigue because, according to the Modality Appropriateness hypothesis (Welch & Warren, 1980), vision is accorded lower priority than audition in temporal discrimination tasks and fatigued individuals tend to focus less on the less preferable modality (Hockey, 1997, 2011). This hypothesis has been confirmed. Furthermore, in accordance with our expectations regarding cross-modal conflicts, we found that the interfering effect of auditory distractors on visual duration judgments increased over time but the interfering effect of visual distractors on auditory processing did not increase. These results suggest that as participants became fatigued, they focused more on the modality that better suited the temporal nature of the task (i.e. the auditory modality) leading to diminished performance on the visual trials. This interpretation gained further support from the analysis of cardiac measures, because both the decreasing trend of heart rate and the increasing trend of vagally-mediated HRV indices suggest that participants did not exert additional effort to maintain task performance, which would have manifested in increased heart rate but changed their strategy. The findings regarding HRV also provide further evidence for an increased parasympathetic activity under fatigue that was found in Study 2 as well.

Finally, the aim of the fourth study was to apply machine-learning algorithms trained on HRV data for fatigue detection and for the estimation of subjective fatigue following prolonged cognitive performance. When trained on task-related HRV data, classification models detected fatigue with an accuracy of approximately 75%, which is comparable with the performance of the models presented in previous studies (Laurent et al., 2013; Huang et al., 2018). On the other hand, the algorithms trained on resting HRV data performed worse and permutation tests indicated that the prediction accuracy of these models did not exceed chance level accuracy. For both classification problems (i.e. algorithms trained on task-related or resting HRV), the best performance was achieved by the support vector machine algorithm. For the estimation of change in subjective fatigue, we applied regularized regression models and random forest regression. Two resting HRV indices, RMSSD and SD2, the initial level of subjective fatigue and the duration of the task were entered as predictors into the models. The lasso regression and the elastic net regression models showed high levels of predictive accuracy that was confirmed by permutation tests as well.

8. List of publications

Publications related to the thesis

Matuz, A., Van der Linden, D, Kisander, Z., Hernádi, I., Karádi, K., Csathó, Á. (2021). Enhanced cardiac vagal tone in mental fatigue: analysis of heart rate variability in time-on-task, recovery, and reactivity. *PLoS ONE 16*(3): e0238670. (Impact factor: 2.74)

Matuz, A., Van der Linden, D., Topa, K., & Csathó, Á. (2019). Cross-modal conflict increases with time-on-task in a temporal discrimination task. *Frontiers in psychology*, *10*, 2429. (Impact factor: 2.13)

Publications not related to the thesis

Elek, Z., Rónai, Z., Hargitai, R., Réthelyi, J., Arndt, B., Matuz, A., Csathó, Á., Polner, B. & Kállai, J. (2020). Magical thinking as a bio-psychological developmental disposition for cognitive and affective symptoms intensity in schizotypy: Traits and genetic associations. *Personality and Individual Differences*, 110498. (Impact factor: 2.31)

Zsido, A. N., Csatho, A., Matuz, A., Stecina, D. T., Arato, A., Inhof, O., & Darnai, G. (2019). Does threat have an advantage after all? – Proposing a novel experimental design to investigate the advantages of threat-relevant cues in visual processing. *Frontiers in psychology*, *10*, 2217. (Impact factor: 2.13)

Zsido, A. N., Matuz, A., Inhof, O., Darnai, G., Budai, T., Bandi, S., & Csatho, A. (2019). Disentangling the facilitating and hindering effects of threat-related stimuli–A visual search study. *British Journal of Psychology*. (Impact factor: 3.24)

Birkás, B., Matuz, A., & Csathó, Á. (2018). Examining the deviation from balanced time perspective in the Dark Triad throughout adulthood. *Frontiers in psychology*, *9*. (Impact factor: 2.09)

Matuz, A. (2017) A szemantikus feldolgozás féltekei lateralizációja kettős feladatvégzés során: A vigilanciaszint csökkenésének hatásai In: Böhm, G.; Czeferner, D.; Fedeles, T. (szerk.) *Specimina operum iuvenum 5. Szemelvények 4*. PTE-BTK

Presentations and posters related to the thesis

Matuz, A. & Csathó, Á. (2021) Estimating and detecting mental fatigue based on heart-rate variability: a machine learning approach. *DOSZ Egészségtudományi és Innovációs Konferencia,* Budapest (online presentation)

Matuz, A. & Csathó, Á. (2020) Resting or task? - A comparison of machine learning-based mental fatigue detection from resting and task-related heart-rate variability data. *9th Interdisciplinary Doctoral Conference,* Pécs (online presentation)

Matuz, A. & Csathó, Á. (2020) Detection of acute mental fatigue based on heart-rate variability: a machine learning approach. *Medical Conference for PhD Students and Experts of Clinical Sciences,* Pécs (online presentation)

Matuz, A.; Schwarcz, B.; Topa, J. K.; Magyar, T. & Csathó, Á. (2019) Perceived duration of cognitively demanding tasks: the role of cognitive load and time-on-task. *61st Tagung experimentell arbeitender Psychologen*, London, Egyesült Királyság (poster presentation)

Matuz, A.; Topa, J. K. & Csathó, Á. (2018) Resting heart-rate variability predicts susceptibility to mental fatigue in a demanding cognitive task. *19th World Congress of Psychophysiology,* Lucca, Olaszország (poster presentation)

Matuz, A.; Simon, O.; Hernádi, I.; Kisander, Zs.; Karádi, K. & Csathó, Á. (2018) Fatigue and resting related changes in a dual two-back task. *60th Tagung experimentell arbeitender Psychologen*, Marburg, Németország (oral presentation)

Matuz, A.; Simon, O.; Hernádi, I.; Kisander, Zs.; Karádi, K. & Csathó, Á. (2018) A mentális fáradtság és a pihenés hatásai bimodális munkamemória feladatban: pszichofizikai és elektrokardiogram elemzés. *A Magyar Pszichológiai Társaság XXVII. Országos Tudományos Nagygyűlése,* Budapest (oral presentation)

Csathó, Á.; Matuz, A.; Simon, O. & Hernádi, I. (2018) Switching between two modalities under fatigue. *60th Tagung experimentell arbeitender Psychologen*, Marburg, Németország (poster presentation)

Matuz, A. (2018) Szívleljük-e a fáradtságot? – A mentális fáradtság hatása a szívfrekvencia-variabilitásra. *XI. Nemzetközi és XVIII. Országos Interdiszciplináris Grastyán PhD. és TDK Konferencia*, Pécs (oral presentation)

Csathó, Á.; Matuz, A. & Hernádi, I. (2017) Simultaneous attention to visual and auditory information under fatigue. *FENS Regional Meeting*, Pécs (poster presentation)

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