Perceived time drives physical fatigue

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Abstract

Recent studies suggested that fundamental physiological processes, such as physical fatigue, rely on the perceived rather than the actual time. However, the neural correlates underlying this effect and its disentanglement from motivational factors (i.e., performance goals) remain unknown. To investigate the time deception effect on fatigue, we developed a novel EEG design in which participants performed 100 isometric contractions at a fixed pace and resistance per session. The actual contraction duration (short or long) and the calibration of the displayed clock (normal or biased to an acceleration or deceleration) were independently manipulated between sessions to examine whether fatigue and its neural correlates evolved based on perceived or actual time. Our results show an accumulation of physical fatigue that follows the perceived time, irrespective of motivational factors. This effect was consistently observed only when the clock was slowed down. This time deception effect was mediated by an oscillatory dynamic that followed perceived time in frontal (theta- and beta-bands) but not motor areas (beta-band). Further analyses highlighted the key role of the frontal oscillatory dynamics in the effectiveness of the time deception effect on physical fatigue.

Significance statement

Can a clock change the course of physical fatigue? In this study, we addressed this question while controlling for motivational confounds and monitoring EEG-associated power modulations. Our findings demonstrate a slowed-down fatigue accumulation in the presence of a slowed-down clock. This time manipulation effect was driven by a frontal oscillatory dynamic that thoroughly followed the perceived time. These results highlight the direct influence of psychological factors on physiological processes and unveil the neural correlates underlying this effect.

Introduction

The relationship between the mind and body has been a subject of inquiry for centuries (Dijkerman & Lenggenhager, 2018), raising fundamental questions about how mental states influence bodily processes. A prevalent approach to exploring this relationship involves deceptively manipulating participants' beliefs while recording psychophysiological variables (Crum et al., 2011; Crum & Langer, 2007; Jones et al., 2013; Williams et al., 2014). Among the various psychological parameters that can be successfully deceived, manipulating the subjective passage of time has been suggested as particularly relevant because of the trust we routinely place in its measurement (Thönes et al., 2018). This manipulation is typically achieved by covertly altering the clock's speed displayed to participants during a task, either slowing it down or accelerating it (Thönes et al., 2018). For instance, when the passage of time is artificially slowed down, studies have reported a reduced perceived pain in response to thermal stimulation (Pomares et al., 2011) but also a smaller decrease in blood glucose level (Park et al., 2016) and slower healing (Aungle & Langer, 2023). Similarly, studies interested in physical activity have shown that, in the presence of a slowed-down clock, there is a slower spontaneous motor activity (Craik & Sarbin, 1963) and a slower accumulation of physical fatigue (Matta et al., 2024). Conversely, accelerating the perceived passage of time has been associated with opposite effects, with the notable exception of physical fatigue, which remains, to our knowledge, unexplored in this context.

Although these perceived time-dependent effects are being demonstrated for several variables (Thönes et al., 2018), their underlying neural mechanisms remain poorly understood. Moreover, motivational factors, such as performance goals, are critical confounds often unaccounted for when measuring deceptive effects. These confounds are particularly important in physical fatigue, in which previous studies have consistently employed deceptive manipulations to enhance physical performance (i.e., the amount of time a task to exhaustion is maintained or the time needed to complete a given distance) (Ansdell et al., 2018; Ducrocq et al., 2017; Matta et al., 2024). Consequently, previous results on physical fatigue may be alternatively explained by performance-related goals rather than time perception.

In the current study, we investigate the neural correlates associated with the time deception effect on the accumulation of physical fatigue, and we carefully isolate this effect from motivational confounds. In addition, we also test its temporal symmetry, that is, when the clock is either slowed down or accelerated. To this end, we used an original 2×2 design, where each session consisted of performing 100 isometric contractions at a given pace against a fixed

individualized resistance. The contraction's actual duration (short or long) and the calibration of the displayed clock (normal or biased toward acceleration or deceleration) were manipulated between sessions to test whether physical fatigue was evolving according to the perceived (i.e., displayed) or actual time (Fig 1A). Unlike previous studies, we tested all four possible combinations for the first time in a within-subject design. We recorded EMG and EEG signals to assess fatigue accumulation and associated neural correlates. Regarding EEG, we specifically looked at the oscillatory dynamics within the motor cortex (MC) and the prefrontal cortex (PFC), as both regions are involved in physical fatigue and effort maintenance (Bigliassi & Filho, 2022; Matta et al., 2025; McMorris et al., 2018; Robertson & Marino, 2016).

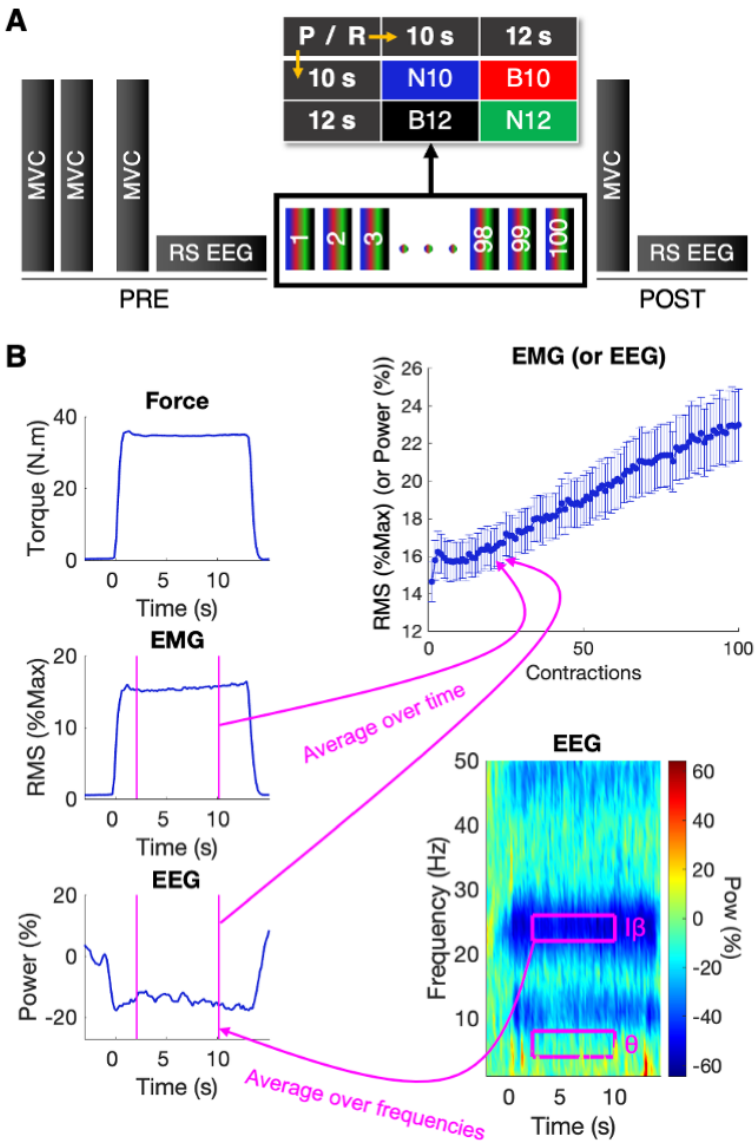

Figure 1 – Experimental protocol and EMG/EEG computation

A. Experimental Protocol. All participants performed 100 contractions during four separate sessions. While the rest time between contractions was identical (5s) for each session, each contraction's real (R) and perceived (P) time were manipulated. In each session, the contractions' time was either short (10s) or long (12s), while the digital

clock displayed in front of the participants was either Normal (N) or Biased (B). Before and after the task, Maximal Voluntary Contractions (MVC) were performed to assess the fatigue generated by the 100 contractions. Resting State (RS) EEG (3 min) was recorded before and after the task to quantify the associated EEG correlates. B. EMG/EEG Computation. All panels represent the typical trace of one contraction except the upper right panel, which illustrates the whole task. EMG and EEG were recorded throughout the task and explicitly analyzed over a 2 to 10 s window within each contraction (0 s being the contraction onset), from which we extracted one average value for each contraction. The EMG was computed in normalized Root Mean Square (RMS), while we computed the mean power of the theta (θ) and an individualized beta-band (Iβ) for the EEG (see Methods for details).

Results

Design Summary

Participants performed four sessions (each spaced 3 to 10 days apart) of 100 quadriceps isometric contractions, during which EMG and EEG were continuously recorded. For each participant, the contraction intensity was identical across sessions (≤ 20% of the participant's maximal force; see Methods for details). While the rest time between contractions was identical for each session, each contraction's real (R) and perceived (P) time were independently manipulated. In each session, the contractions' time was either short (10 s) or long (12 s), while the digital clock displayed in front of the participants was either Normal (N) or Biased (B), leading to 4 counterbalanced conditions: N10 (10s P, 10s R), N12 (12s P, 12s R), B10 (10s P, 12s R), B12 (12s P, 10s R) (Fig 1). Before and after the task, participants performed Maximal Voluntary Contractions (MVC) and 3-minute EEG resting states.

Neuromuscular fatigue

We first compared the physical fatigue generated in the two sessions with unbiased clocks (i.e., N12 and N10 sessions) to confirm that a longer effort generated a measurable difference in neuromuscular fatigue. To this end, we computed the difference between each session's maximal voluntary torque pre-post variation rates and, as expected, we found a significantly negative difference ($t_{(23)} = 1.84$, $p = .039$, $d_z = 0.38$, $BF = 1.75$), indicating greater physical fatigue in the N12 session compared to the N10 session (Fig 2A, 2C). We then applied the same analysis to the B10-N10 and N12-B12 differences, thus comparing the sessions with the same subjective time but different real times. Remarkably, we found no difference between the B10 and N10 sessions ($t_{(23)} = 0.66$, $p = .52$, $d_z = 0.14$, $BF = 0.26$), suggesting similar levels of fatigue between the two, despite the B10 session having a longer amount of actual work, identical to the N12 one. However, this subjective time-dependent relationship was non-

symmetric, as evidenced by a significantly negative difference between the N12 session and the one perceived as long but identical to the short session, namely B12 ($t_{(23)} = 2.82$, $p = .010$, $d_z = 0.58$, BF = 4.99). This comparison indicates more fatigue in the N12 session (Fig 2A, 2C), consistent with its higher actual workload.

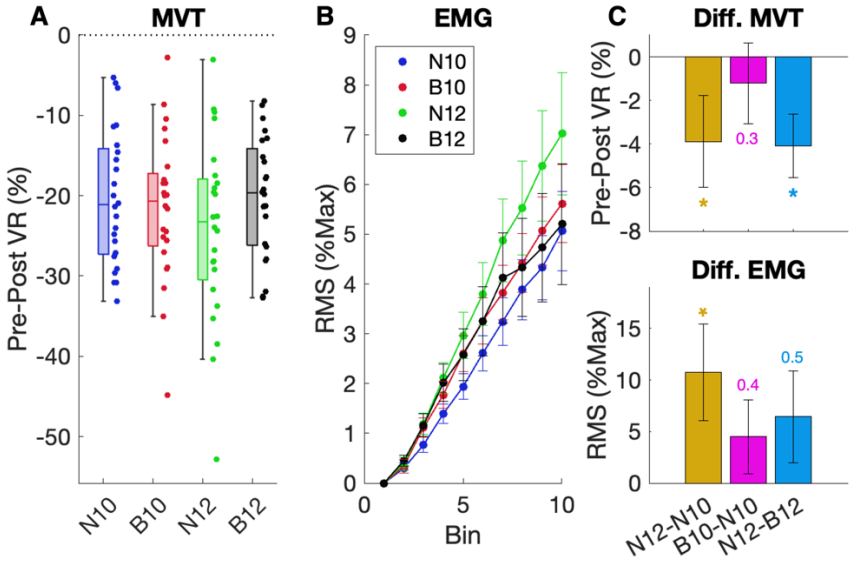

Figure 2 – Physical Fatigue

A. Torque Pre-Post Variation Rate (VR). A decrease in Maximal Voluntary Torque (MVT) reflects a decline in the maximal force production. B. EMG modulations over the main task. EMG is expressed in normalized Root Mean Square (RMS) over contractions, whose increase reflects neuromuscular fatigue accumulation. The dots represent the averaged distribution, and the error bars are the standard error of the mean (SEM). C. Fatigue differences computed for each pair of interest (N12-N10; B10-N10; N12-B12). The upper panel represents the difference for the Pre-Post VR of the MVT, while the lower one contains the difference for the sum of the EMG-RMS over the bins. The bar plots represent the averaged distribution; the error bars are the SEM. Asterisks denote a significant effect with $p<0.05$. The Bayes Factor (BF), rounded to the decimal, was reported when there was no significant difference.

We then investigated whether the biased clock influenced physical fatigue during the task, as observed in the pre-post measurements. To this end, we considered the sum of the EMG Root Mean Square (RMS) activity recorded during each session (Kim et al., 2007; Merletti et al., 1991). As in the pre-post case, we found a significantly positive difference between the N12 and N10 sessions ($t_{(23)} = 2.28$, $p = .016$, $d_z = 0.47$, BF = 3.64), supporting a greater fatigue accumulation in the longer, normal session. Concerning the comparison between the sessions with the same perceived time but a different real one, we found no differences between the subjectively short ones (B10-N10: $t_{(23)} = 1.26$, $p = .22$, $d_z = 0.26$, BF = 0.43), as well as between the subjectively long ones (N12-B12: $t_{(23)} = 1.44$, $p = .16$, $d_z = 0.29$, BF = 0.53) (Fig 2B, 2C). Together, these results indicate that physical fatigue follows perceived rather than actual time

when the clock is slowed down (Matta et al., 2024), whereas the results appear less compelling when the clock is accelerated.

Power modulations in the motor cortex

After demonstrating that physical fatigue depends on perceived time, consistently when the clock is slowed down but less clearly when it is accelerated, we investigated the neural correlates underlying this effect. We first examined the Motor Cortex (MC) activity, a key region involved in executing voluntary contractions (Brown, 2000; Pearson, 2000). In line with previous work (Dal Maso et al., 2012; Forrester et al., 2006), we considered the Cz electrode and assessed relative spectral power changes in each participant's individualized beta-band (Iβ) (Matta et al., 2025) (i.e., a 5 Hz spectral window in the beta band with the largest desynchronization, see Methods for details). Importantly, we found an absence of difference between the N12 and N10 sessions ($t_{(23)} = 0.46$, $p = .33$, $d_z = 0.094$, $BF = 0.32$), possibly due to the relatively small discrepancy between the two sessions' workload (Matta et al., 2025). Similarly, we found no difference between all pairs of sessions with the same subjective time ($p > .65$, $d < 0.093$, $BF < 0.24$) (Fig 3A, 3B).

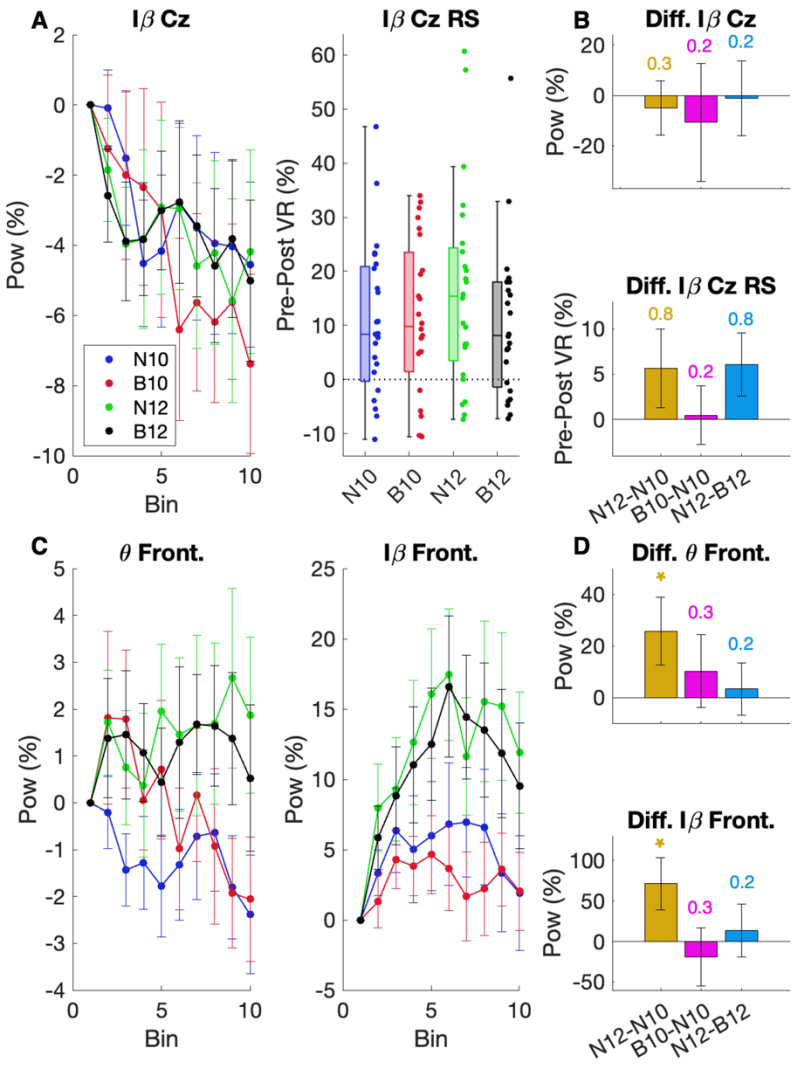

Figure 3 – Neural correlates of time deception

A. EEG Power modulations in the Cz electrode. Panel 1 represents relative power changes over contractions (respective to the first contractions) quantified in an individualized beta-band (Iβ) (see Methods for details). The dots represent the averaged distribution, and the error bars are the standard error of the mean (SEM). Panel 2 represents the Resting State (RS) power Pre-Post Variation Rate (VR) quantified in Iβ. B. Power differences between conditions in the Cz electrodes (N12-N10; B10-N10; N12-B12). The upper panel represents the difference for the sum of the Iβ Cz over the bins, while the lower one contains the difference for the Pre-Post VR of the Iβ Cz RS. C. EEG Power modulations in frontal electrodes. Relative power changes in θ (panel 1) and Iβ (panel 2) over contractions (respective to the first contractions). For both panels, the dots represent the averaged distribution, and the error bars are the SEM. D. Power differences in the frontal electrodes. Power differences were computed for each pair of interests (N12-N10; B10-N10; N12-B12). The upper and lower panels represent the difference in the sum of the frontal θ and Iβ power over the bins, respectively. For B. and D., the barplots represent the averaged distribution, and the error bars are the SEM. Asterisks denote a significant effect with $p<0.05$. The Bayes Factor (BF), rounded to the decimal, was reported when there was no significant difference.

We additionally looked at the Cz electrode's pre- to post-resting states (RS) Iβ power changes. Aligning with our previous results showing a consistent absence of physical fatigue difference between the sessions with a perceived short time, we found no difference between B10 and N10 Iβ power pre-post changes ($t_{(23)} = 0.15$, $p = .89$, $d_z = 0.030$, BF = 0.22). Other comparisons were found to be statistically inconclusive (N12-N10: $t_{(23)} = 1.30$, $p = .10$, $d_z = 0.27$, BF = 0.81; N12-B12: $t_{(23)} = 1.72$, $p = .099$, $d_z = 0.36$, BF = 0.80), though both showed a trend towards a significant difference (Fig 3A, 3B), overall reflecting the same pattern observed in the MVT results (Fig 1A, Fig 1C).

Power modulations in the prefrontal cortex

Next, we investigated changes in prefrontal cortex (PFC) activity, as it has been proposed to play a key role in effort maintenance (Bigliassi & Filho, 2022; Denis, 2020; McMorris et al., 2018; Robertson & Marino, 2016). We analyzed relative spectral power changes in the theta (θ) and Iβ bands of the averaged F3, F4, F7, and F8 electrodes (Okamoto et al., 2004; Robertson & Marino, 2015). While frontal θ is assumed to reflect cognitive control (Cavanagh & Frank, 2014), the β band has also been proposed to have a similar function (Stoll et al., 2016). We found a significantly positive N12-N10 difference in both the θ ($t_{(23)} = 1.96$, $p = .031$, $d_z = 0.40$, BF = 2.10) and Iβ bands ($t_{(23)} = 2.23$, $p = .0.018$, $d_z = 0.45$, BF = 3.29). Remarkably, we also found that the sessions with the same perceived time did not exhibit any power difference for both bands (B10-N10, θ: $t_{(23)} = 0.72$, $p = .48$, $d_z = 0.15$, BF = 0.27; Iβ: $t_{(23)} = 0.54$, $p = .60$, $d_z = 0.11$, BF = 0.25); B12-N12, θ: $t_{(23)} = 0.33$, $p = .75$, $d_z = 0.066$, BF = 0.23; Iβ: $t_{(23)} = 0.42$, $p = .68$, $d_z = 0.085$, BF = 0.23)) (Fig 3C, 3D), indicating a strong dependency of these variables on perceived rather than actual time. Differently than in the MC, for which we did not observe an influence of the time manipulation, these results suggest a key role of the oscillatory activity of the PFC in the perceived time-dependent fatigue accumulation.

EEG-EMG Connectivity

After independently investigating the EMG and the EEG power modulations, we considered the link between them by computing subject-by-subject correlations. We first found consistently across participants a negative correlation between EMG and Iβ Cz for all sessions ($p < .045$, $d > 0.43$, BF > 1.41) (Fig 4A), indicating more EMG activity for larger Iβ desynchronization. We then investigated the link between EMG and frontal oscillatory activity. Similarly, we found a negative correlation between EMG activity and frontal θ-band oscillations in B10 ($t_{(23)} = 2.70$, $p = .013$, $d_z = 0.46$, BF = 3.96), and as a trend in N10 ($t_{(23)} = 1.99$, $p = .059$, $d_z = 0.41$,

BF = 1.14), but no correlations in the N12 and B12 sessions ($p > 0.36$, $d < 0.19$, $BF < 0.32$) (Fig 4B). Conversely, we found a positive correlation between the EMG activity and the Iβ in the B12 session ($t_{(23)} = 2.25$, $p = .035$, $d_z = 0.46$, $BF = 1.74$) and, as a trend, in the N12 one ($t_{(23)} = 1.75$, $p = .094$, $d_z = 0.36$, $BF = 0.80$), while there was no correlation in the sessions whose perceived time was shorter (N10 and B10, $p > 0.75$, $d < 0.66$, $BF < 0.23$, for both) (Fig 4C). These results mirror the trends observed in frontal power modulations (Fig 3C), showing lower PFC-EMG correlations for short perceived times and larger correlations for longer ones, suggesting their dependency on perceived rather than actual time.

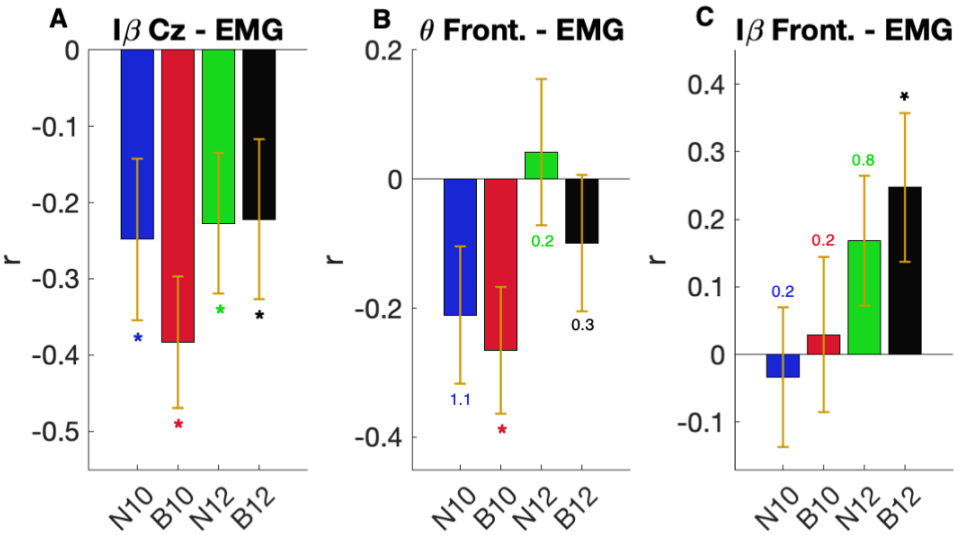

Figure 4 – Brain-muscle correlations

Within-subject correlations were performed between EMG and θ Frontal (A), Iβ Cz (B), and Iβ Frontal (C), respectively. The resulting r values were then compared against 0 using t-tests. The barplots represent the averaged distribution, and the error bars are the standard error of the mean. Asterisks denote a significant effect with $p<0.05$. The Bayes Factor (BF), rounded to the decimal, was reported when there was no significant difference.

Relationship between frontal oscillatory dynamics and fatigue accumulation

Our results show a perceived time-dependent accumulation of physical fatigue and a frontal oscillatory dynamic that thoroughly follows perceived rather than actual time. Starting from the assumption that PFC is involved in belief representation (Geuter et al., 2017), we hypothesized that participants with the strongest deceptive effect in the PFC would also exhibit the most substantial effect in the EMG. To test our hypothesis, we split the participants twice into two groups, via a median split, computed on the normalized θ power difference between the two sessions with the same perceived time. Such differences were computed as the absolute sum of the θ power difference between the B10-N10 and the N12-B12 sessions, normalized by the difference between the N12 and N10 conditions. In both cases, smaller differences correspond

to a larger deceptive effect, as the θ power modulation in PFC follows the perceived rather than the actual time ('Subjective-time' (ST) group in Fig 5). Conversely, participants with larger power differences would rely more on the actual rather than the perceived time ('Objective-time' (OT) group in Fig 5). Note that we used the θ power difference to perform our median split due to its well-established relationship to cognitive control (Cavanagh & Frank, 2014).

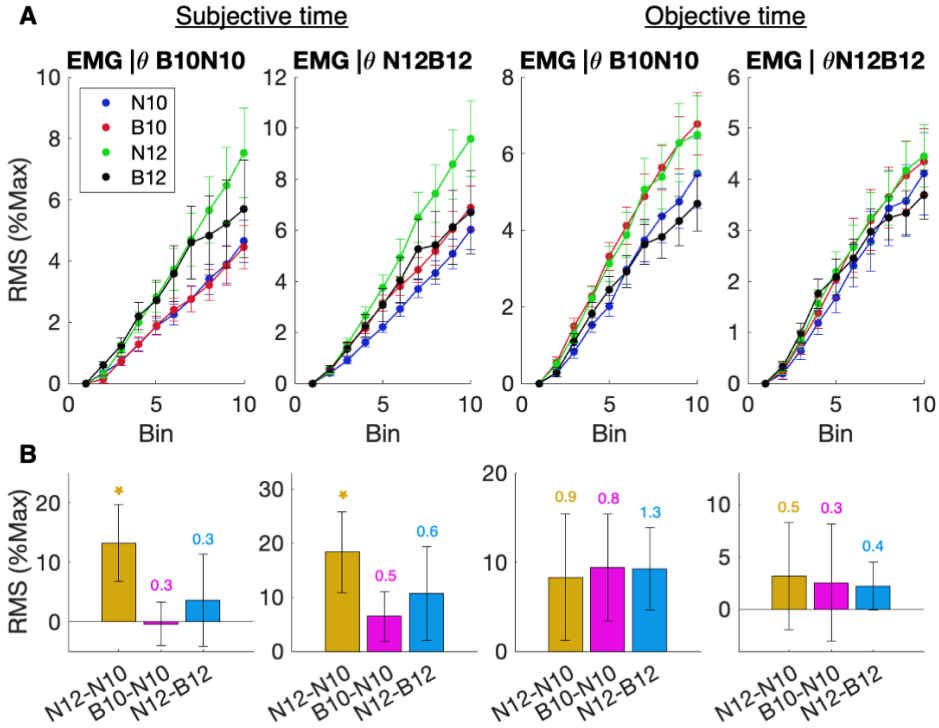

Figure 5 – Physical fatigue accumulation regarding frontal oscillatory dynamics

A. EMG modulations over the main task. EMG is expressed in normalized RMS over contractions, whose increase reflects neuromuscular fatigue accumulation. Panels 1 and 2 contain the 'Subjective-time' participants, and panels 3 and 4 the 'Objective-time' ones (based on the deception effects measured in the θ-band, see text for details). Panels 1 and 3 were computed on the B10-N10 frontal θ absolute sum power difference and Panels 2 and 4 on the N12-B12 one. For all panels, the dots represent the averaged distribution, and the error bars are the standard error of the mean (SEM). B. EMG differences. EMG differences were computed for each pair of interest (N12-N10; B10-N10; N12-B12). Each panel is computed based on the sum of the EMG represented above it. For all panels, the barplots represent the averaged distribution, and the error bars are the SEM. Asterisks denote significant effect with $p<0.05$. The Bayes Factor (BF), rounded to the decimal, was reported when there was no significant difference.

The ST group was the only one showing a significant positive difference between N12 and N10 in the fatigue accumulation as reflected by the EMG activity (ST: $p < .033$, BF > 2.58, OT: $p > 0.13$, BF < 0.86). Remarkably, when considering the θ-band power difference between B10-N10 conditions to split participants, we found an absence of difference between B10 and N10

($t_{(11)} = 0.11$, $p = .91$, $d_z = 0.033$, BF = 0.29), as well as between N12 and B12 ($t_{(11)} = 0.47$, $p = .65$, $d_z = 0.13$, BF = 0.32) for the ST group in their EMG response. Further considering the θ-band power difference between N12-B12 conditions to split participants, we also found a trend for an absence of difference for the two sessions with the same perceived time ($p > .19$, BF < 0.63 for both B10-N10 and N12-B12) for the ST group. Conversely, the OT group showed no difference for any pairs of sessions, regardless of the power differences considered to split participants ($p > 0.27$, BF < 1.25 for all) (Fig 5A,5B). Together, these results suggest that the power changes occurring within the PFC play a key role in the effectiveness of the deceptive effect on fatigue accumulation, as measured by the EMG. Interestingly, it also reveals that, in the ST group, fatigue can be slowed down and accelerated.

Link between interoceptive awareness and deception

To further explore the individual differences that may affect the strength of the deceptive effect, we considered as a mediating parameter the participants' interoceptive awareness, which was measured via the Multidimensional Assessment of Interoceptive Awareness (MAIA) (Mehling et al., 2012) after their last session. We specifically focused on the 'Noticing' and 'Body Listening' subscales, which are more closely linked to bodily processes (Iodice et al., 2019). We then tested the correlation between the Noticing and Body Listening scores with the normalized absolute difference of neuromuscular fatigue accumulation (i.e., EMG) for the two sessions with the same subjective time (B10-N10 or N12-B12). In short, a low normalized index indicates no difference between the two sessions, suggesting a large deceptive effect, while a high index reflects the opposite. We hypothesized a positive correlation between the interoceptive score and the normalized index, i.e., the lower the interoceptive awareness, the higher the deceptive effect, and vice-versa. Using non-parametric Kendall's tau correlation, we found a positive correlation between the Body Listening score and the B10-N10 normalized difference only ($\tau = 0.29$, $p = 0.029$, BF = 3.16, unilateral test, H1: positive correlation). No correlation was found with the Noticing score ($p > 0.27$, BF < 0.47). These results suggest that the participant's body awareness might predict the deceptive effect on neuromuscular fatigue accumulation in the slow-down clock configuration.

As our findings previously suggested a role of the PFC in the deceptive effect, we tested the correlation between the Noticing and Body Listening scores with the normalized absolute difference of θ frontal power modulations for the two sessions with the same perceived time. We found a positive correlation between the Body Listening score and the N12-B12 θ normalized difference only ($\tau = 0.31$, $p = 0.020$, BF = 4.30, unilateral test, H1: positive

correlation). While this result supports a link between interoception awareness and the deceptive effect, it remains unclear why it only appears when time is accelerated but not slowed down, as no other significant correlations were found ($p > 0.11$, $BF < 1.02$, unilateral test, H1: positive correlation).

Discussion

In the current study, we used a novel design to test the influence of time deception on physical fatigue accumulation while monitoring associated EEG power modulations. We found that physical fatigue consistently evolved according to the perceived rather than the actual time when the clock was slowed down, while it was not systematic for the accelerated clock. Importantly, this deceptive effect was found in the absence of motivational confounds, demonstrating for the first time the direct influence of time deception on the course of physical fatigue. Regarding the neural correlates of the deceptive effect, we observed no significant impact in the MC, possibly due to a relatively small difference in workload between the sessions. However, we found that frontal oscillatory dynamics thoroughly followed the perceived time. We then showed that frontal dynamics predict the effectiveness of time deception on fatigue accumulation, suggesting a key role of the PFC in the time deception effect.

Physical fatigue follows the perceived time

Our findings reveal that physical fatigue follows the subjective rather than the objective time when the clock is slowed down, echoing previous work emphasizing the mind's influence on bodily processes (Craik & Sarbin, 1963; Crum et al., 2011; Crum & Langer, 2007; Langer et al., 2010; London & Monello, 1974; Pomares et al., 2011; Schachter & Gross, 1968; Snyder et al., 1974; Thönes et al., 2021), such as blood glucose level (Park et al., 2016) and healing (Aungle & Langer, 2023). While physical fatigue has been proposed to depend on subjective time (Matta et al., 2024), the current study is the first to accurately disentangle the motivational effects from the temporal deception. Furthermore, our results seem to show an asymmetrical effect regarding clock manipulation. A possible explanation may involve efficiency considerations, as slowing down the process that conducts to exhaustion appears effective in fulfilling the required task (Meyniel et al., 2013), while accelerating it may be counterproductive. However, complementary analyses (Fig 5) nuance this effect, showing that some of the participants rely more on perceived time, both when the clock was slowed down and accelerated, while others follow objective time. Our findings suggest that interoceptive awareness mediates this effect: lower interoceptive awareness is associated with a larger deceptive effect, and vice versa. However, other factors likely influence this perceived-time dependency, such as the strength of participants' beliefs (e.g., expectations that shorter times lead to less fatigue) (Shiv & Carmon, 2005), the effectiveness of external clock manipulations

on the perception of time (Craik & Sarbin, 1963; Thönes et al., 2018), but also participants' backgrounds or personality (Zhou et al., 2019). Further research is needed to better characterize the factors driving time deception's effectiveness on fatigue.

Neural correlates of the time deception effect

In the current study, we found no differences between sessions in the MC oscillatory dynamics, likely due to a relatively small workload difference (Matta et al., 2025), making any potential difference due to the deceptive manipulation even more challenging to observe. Yet, these parameters were carefully chosen to ensure the implicit plausibility of the biased clock calibration, as increasing the manipulation's magnitude could have raised awareness of the effect, potentially negating and confounding its impact (Ducrocq et al., 2017; Williams et al., 2014).

Even though the task constraints imposed a relatively short temporal difference between conditions, we nevertheless found a significant effect reflected in theta and beta frontal oscillatory dynamics, which follow perceived rather than actual time. Interestingly, both theta and beta-band activity increases have been previously associated with prolonged engagement in demanding tasks (Boksem et al., 2005; Stoll et al., 2016). Specifically, enhanced theta power has been extensively linked to increasing mental (Baumeister et al., 2012; Borghini et al., 2014; Craig et al., 2012; Fan et al., 2015; Käthner et al., 2014; Liu et al., 2010; Shigihara et al., 2013; Tanaka et al., 2014; Wascher et al., 2014) and, albeit less consistently, physical (Bailey et al., 2008; Hottenrott & Gronwald, 2013; Mechau et al., 1998) fatigue – both supposedly sharing common neural resources (Bray et al., 2012; Jin et al., 2024; Marcora et al., 2009; Mehta & Parasuraman, 2014; Van Cutsem et al., 2017). This increase in theta power has been proposed as reflecting a fatigue-related compensatory mechanism (Wascher et al., 2014) to allow sustaining performance, seemingly driven by subjective rather than actual performance. Moreover, given that frontal theta is a well-established marker of cognitive control (Arnau et al., 2024; Cavanagh et al., 2012; Cavanagh & Frank, 2014; Ehrhardt et al., 2022; Howells et al., 2010; Huster et al., 2013; Ishii et al., 1999; Lopez-Gamundi et al., 2024; McFerren et al., 2021; Yu et al., 2022), our results suggest that the cognitive control required to sustain a physical task depends on perceived rather than actual time. Finally, several studies also reported an increase in frontal beta with the rise in fatigue (Bailey et al., 2008; Enders et al., 2016; Hottenrott & Gronwald, 2013; Kubitz & Mott, 1996; Mechau et al., 1998). This increase might also reflect a top-down cognitive control (Buschman & Miller, 2007; Stoll et al., 2016) allowing one to continue the task despite uncomfortable sensations, which might follow perceived rather

than actual time. Together, these results highlight the reliance of specific cognitive control time-related correlates to perceived rather than actual time. Additionally, it emphasizes the importance of considering subjective components in cognitive experimental paradigms, as various subjective factors may significantly influence physiological measures.

A predictive coding perspective

We found that PFC oscillatory dynamics and physical fatigue evolve according to perceived rather than actual time. The influence of the PFC on physical fatigue may be explained through predictive coding (Kaptchuk, 2018), a framework suggesting that the brain continuously generates expectations about incoming sensory information (Friston, 2010). When there is a mismatch between expected and actual sensations – a prediction error – the brain can resolve this discrepancy either by updating its expectations (priors) or by actively adjusting bodily states (active inference) (Friston et al., 2009; Pezzulo et al., 2015; Seth, 2013). If we apply this framework to our findings, we may consider beliefs about time as prior factors that regulate physical fatigue through an active inference process. In this situation, the temporal deceptive manipulation induces an inaccurate temporal estimate, which generates a prediction error in the participants about their current fatigue level. In order to minimize such prediction error – the discrepancy between expected and actual fatigue – the brain may modulate interoceptive input (i.e., interoceptive signals related to physical fatigue, later influencing EMG signals), thereby adjusting the evolution of physical fatigue rather than revising its priors (Pagnini et al., 2023). In line with this framework, frontal oscillatory dynamics could reflect temporal priors, as the PFC has been proposed to play a key role in this process (Geuter et al., 2017). Furthermore, previous research has demonstrated that beliefs can influence physiological effector systems such as the autonomic nervous system (Amigo et al., 1993; Meissner, 2009, 2011; Nakamura et al., 2012; Wager et al., 2009). In line with this interpretation, one may speculate that the change in the physical fatigue course is mediated by an indirect pathway that originates in the PFC and regulates peripheral organs (e.g., cardiac, respiratory) (Hassan et al., 2013; Thayer et al., 2009, 2012), impacting muscle fatigue as an outcome to reduce the prediction error. Furthermore, our complementary analysis, splitting the participants based on their PFC power difference between sessions with the same subjective time, support the hypothesis that frontal areas modulate the time manipulation effect. Indeed, as shown in Figure 5, only participants exhibiting strong deceptive effects in the PFC also experienced the deceptive effect on fatigue, as revealed in the EMG recordings. This result may pinpoint the PFC as one of the core structure involved in mediating the time deception effects on physical fatigue.

Conclusion

Our study demonstrates the direct influence of time deception on physical fatigue, irrespective of motivational factors and performance goals, and reveals key neural correlates of this effect. We show that this influence is primarily mediated by frontal oscillatory dynamics, which thoroughly follow the perceived time and are pivotal to the effectiveness of such deceptive time manipulation. Building on these findings, we propose potential mechanisms underlying this mind-body interaction. Future research will further investigate the neural mechanisms driving this phenomenon from different perspectives (e.g., cardiac, respiratory or fMRI recordings), to further deepen its theoretical understanding and explore its potential applications to clinical conditions.

Methods

Participants

Twenty-eight healthy volunteers (16 women, age: 24 ± 4, weight: 70 ± 18, mean ± SD) with no known history of neurological diseases or physical injuries and regular physical practice (once to several times a week) participated in this study. Out of the 28 individuals, 24 were able to complete the entire protocol and were kept on for the analysis. Before participating in the study, all individuals provided informed consent and were informed of their right to withdraw from the study at any time. The study procedure was approved by the French Ethical 'Comité de Protection des Personnes' (number: 2023-A00412-43).

Data Acquisition

During each session, all participants were seated on a Biodex isokinetic ergometer with their hips and knees bent to a 90° angle. Their right leg was securely fastened to the ergometer accessory at the ankle with a non-compliant strap just above the malleolus. Two shoulder and one abdominal harnesses guaranteed a reduction in their range of motion and the involvement of other muscles besides the quadriceps. The installation parameters were optimized for every subject individually and kept identical within subjects for each session.

Torque and electromyography (EMG) were recorded at 2000 Hz using a Biopac MP150 system and AcqKnowledge software. EMG was recorded through three pairs of electrodes (AG-Cl, diameter: 11 mm, interelectrode distance: 2 cm), which were placed on the Vastus Medialis, Vastus Lateralis, and Rectus Femoris according to SENIAM recommendations. Before placement, the skin was carefully prepared through shaving and alcohol to ensure low impedance (<5 KΩ). The reference electrode was positioned on the patella of the contralateral knee. EEG was recorded using a 64 electrodes Biosemi Active 2 system with 64 Ag-AgCl sintered active electrodes at 2048 Hz. The EEG electrode locations followed the 10–20 international system. The offset was kept below 20 mV using an active gel. All acquisitions were performed with the light off to minimize electrical noise.

The main task was programmed in Python and displayed through a Windows computer (Resolution: 1920 × 1080; Refresh rate: 60 Hz), using a NiDAQ acquisition card (NI USB-6218, Sample rate: 2000 Hz) to read the torque data (low-pass filtered at 10 Hz) in real-time. The same computer also generated the triggers used to mark the onset and offset of each contraction towards BIOPAC and BIOSEMI, allowing us to synchronize all our signals offline.

Experimental Protocol

All participants came to the lab on four days (each spaced 3 to 10 days apart) to perform four sessions. On each day, the participants performed the following steps (Fig 1):

- Warm-up (consisting of 15-20 contractions with increasing intensity, approximately from 20 to 80% of their estimated Maximal Voluntary Torque (MVT))
- 2 Maximal Voluntary Contractions (MVC) (3-4 s each, 30 s spaced)
- 1 MVC, 20 s of rest, 1 Long MVC (30 s), 30 s of rest, 3 minutes of EEG recording at rest (eyes opened)
- 5 minutes of rest
- Main task: 100 contractions (see below)
- 1 MVC (5 s after the 100th contraction of the main task), 20 s of rest, 1 Long MVC (30 s), 30 s of rest, 3 minutes of EEG recording at rest (eyes opened)

Regarding the main task, participants performed 100 contractions at a fixed individualized intensity, defined as 20% of their maximal force, or 40 N.m if their maximal force was larger than 200 N.m. The intensity was the same among the four sessions. While the rest time between contractions was identical for each session (5 s), each contraction's real (R) and perceived (P) time were independently manipulated. In each session, the contractions' time was either short (10s) or long (12s), while the clock displayed to the participants was either Normal (N) or Biased (B). This manipulation led to 4 counterbalanced conditions: N10 (10s P, 10s R), N12 (12s P, 12s R), B10 (10s P, 12s R), B12 (12s P, 10s R). In practice, a sound indicated to the participants when to begin and end each contraction. Simultaneously with the starting sound, a rectangle was displayed in the middle of a black screen to provide online feedback to the participants on their actual force compared to the individualized targeted one. The rectangle's color was updated online according to the ongoing force produced: red indicated that participants were below the targeted force, blue above, and green in the aimed range (-5% to +5% around the targeted force). A digital clock was displayed in the middle of the colored rectangle 0.75 s after the start of the contraction (preparation time left to the participants to reach the targeted force). This clock allowed us to perform our manipulation: it was either normal (N10 and N12), slowed down (B10), or accelerated (B12) without the participants knowing it. After the ending sound, the final perceived time (10.0 or 12.0 s) remained on the screen for 1 s, then the number of contractions already performed was displayed during the resting time. Note that data from the two normal sessions (N10 and N12) have been previously reported (Matta et al., 2025) in the context of a different question; Long MVC were specifically used there.

Data pre-processing

All data pre-processing and analyses were conducted offline using custom MATLAB (version 2022b) scripts along with EEGLAB functions (Delorme & Makeig, 2004). Torque and EMG data were down-sampled offline to 1000 Hz. Torque data were then low-pass filtered at 10 Hz, while EMG data underwent band-pass filtering between 20 and 500 Hz and notch filtering between 47 and 53 Hz.

EEG data were down-sampled offline to 250 Hz. A notch filter (47 to 53 Hz) and a high-pass filter with a 1 Hz cut-off frequency were applied. Channels with excessive noise were automatically rejected using the CleanRawData plugin, configured with a 5-second 'flat line criterion,' a 0.6 'minimum channel correlation,' and a kurtosis threshold exceeding five times the mean. On average, 61.7 ± 1.8 (mean ± SD) channels were retained for analysis. The electrodes were then re-referenced using a common average reference. Independent Component Analysis (ICA) was performed with the Infomax algorithm, and the resulting components were labeled using the ICLabel plugin (Pion-Tonachini et al., 2019). Components labeled as muscle, eye, heart, line noise, channel noise, or other with a probability above 90% were automatically rejected, averaging 12.9 ± 5.5 components removed. Previously excluded channels were subsequently interpolated.

EEG data from the two resting-state periods were segmented into 2-second non-overlapping windows. For the main task, EEG and EMG data were segmented into 18-second epochs, starting 3 seconds before the onset of the contraction (as marked by its trigger) and ending 15 seconds after. A final epoch rejection procedure was applied to the main task EEG data to remove additional noise. Epochs with a standard deviation greater than 1.5 times the interquartile range (IQR) above the 3rd quartile or below 1.5 times the IQR under the 1st quartile were rejected for each subject and electrode. This procedure eliminated 3.9% of the epochs over the four sessions.

Data analysis

Force and EMG

<u>Pre-Post.</u> The highest torque from the three MVCs performed before the task was used to determine the pre-test Maximal Voluntary Torque (MVT). The post-test measurement was taken as the highest torque recorded during the post-task MVC. The variation rate was calculated as (post – pre)/pre ×100.

Main Task. EMG was quantified as the root-mean-square (RMS) during each contraction of the main task from 2 to 10 seconds after the onset of the contraction (Fig 1). This period was chosen to exclude the beginning of the contraction, where torque stabilization has not yet occurred, and to ensure identical comparison times for all sessions. Within this period, EMG was quantified as the RMS over 180 ms non-overlapping windows, normalized by the RMS EMG associated with the previously selected maximal torque (centered from -90 ms to +90 ms around it) for the respective muscle and session. The three muscle EMG values were averaged over time to yield one EMG value per contraction in the main task. These EMG values were then averaged in bins of 10 contractions, with the first bin zero-centered, and the sum of the EMG evolution over the task was computed, resulting in a single representative EMG value for each variable and session.

EEG Spectral Power

Spectral power was obtained by applying a continuous wavelet transform to the pre-processed, epoched EEG data within the 1 to 50 Hz frequency range. The wavelet length was linearly increased from one cycle at 1 Hz to twenty cycles at 50 Hz, optimizing the tradeoff between temporal and frequency resolution across the entire frequency range. Contractions that were removed were subsequently linearly interpolated.

Spectral power was specifically extracted for the Theta (θ, 4-8 Hz) and an Individualized Beta band (Iβ), which was defined for each subject to account for inter-individual variability in the beta desynchronization-specific frequency band (Fig 1). Specifically, the frequency with the largest desynchronization was identified for each subject, and Iβ was defined as the range from -2 to +2 Hz around this frequency (Matta et al., 2025). Power from the lateral-frontal (F7-F8) and mid-frontal (F3-F4) electrodes was averaged to create a 'Frontal' cluster, chosen to reflect the ventrolateral and dorsolateral prefrontal cortex (Okamoto et al., 2004; Robertson & Marino, 2015) activity. The Cz electrode was used to reflect motor cortex (MC) activity associated with quadriceps contraction, a location confirmed by topographically visualizing beta desynchronization (Dal Maso et al., 2012; Forrester et al., 2006; Gordon et al., 2023; Meier et al., 2008).

Pre-Post Analysis. Raw spectral powers from pre- and post-EEG resting state recordings were independently averaged over epochs (90) and time (0 to 2 s). The variation rate was calculated between the pre- and post-values for each frequency band and region of interest.

Main Task Analysis. For each contraction, raw spectral power bands during the period of interest (2 to 10 s) were normalized to the first contractions of the session, averaged over the

same 2 to 10 s period (Fig 1). This normalization, focusing on the fatigue effect, involved subtracting the baseline and dividing by it, then multiplying by 100 to express power values as a percentage of a non-fatigued state. The baseline was defined as the average of contractions 2 to 5, excluding the first contraction due to its significant torque variability in both sessions. The resulting values were averaged over time and frequencies, yielding one power value per frequency band, contraction, and region of interest. As for the EMG, values were then averaged in bins of 10 contractions, with the first bin zero-centered. Finally, the sum of the power evolution over the task was eventually extracted, yielding one representative value for each variable and session.

Statistical analyses

All statistical analyses were conducted using frequentist and Bayesian frameworks to properly assess the acceptance of the null hypothesis (Masson, 2011). In the frequentist approach, significance was determined at $p < .05$. In the Bayesian framework, the Bayes Factor (BF) represents the ratio comparing the model supporting the alternative hypothesis to the one favoring the null hypothesis. Conventionally, BFs>~3 provide evidence in favor of the alternative hypothesis, while BFs <~0.3 indicate evidence in favor of the null hypothesis (van Doorn et al., 2021). All statistical analyses were conducted using JASP (2023, version 0.18.2) (Love et al., 2019), with default uniform prior distributions for the Bayesian framework.

Conditions were compared by focusing on specific pairs of interest. First, we examined the difference between N12 and N10, expecting the result to be significantly different from zero (one-sample unilateral t-test), thereby highlighting a difference exclusively attributable to fatigue. Subsequently, we compared the two pairs of sessions with the same perceived time, specifically B10-N10 and N12-B12 (one-sample bilateral t-test), to assess the effect of perceived time on fatigue.

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