

Physiological-Based Change Point Detection During Sustained Attention: A multimodal EEG and Eye-Tracking Study

Naomi Thomas¹, Dalya Al-Mfarej², James Tung²

¹ Biomedical Engineering, University of Waterloo, Waterloo, Canada

² System Design Engineering, University of Waterloo, Waterloo, Canada

E-mail: naomi.thomas@uwaterloo.ca

ABSTRACT: Distinguishing adaptive cognitive effort from fatigue in real-time is critical for optimising task difficulty in motor rehabilitation. This study applies a data-driven change-point detection framework to 60-minute Attention Network Task (ANT) recordings from 7 healthy participants to detect cognitive state transition by integrating spectral and connectivity EEG features, and eye-tracking features. For each participant, 7 classifiers were trained at every candidate split time to identify the temporal boundary at which pre- and post-transition physiological and behavioural states were maximally discriminable. Multimodal fusion of physiological features achieved a mean ROC AUC of 0.933 ± 0.050 , exceeding behavioural features alone by 0.245 AUC units ($t(6) = 17.89, p < 0.001$) on average. The grand mean physiological-based split occurred at 21.6 ± 7.4 minutes, with substantial inter-individual variability (range: 13.4–35.0 min). Post-split exhibited decreased α / α ratios, increased α power, and pupil enlargement, consistent with compensatory effortful processing rather than passive fatigue. The difference between EEG and behavioural based change-point time ($\Delta = 2.9 \pm 14.4$ minutes) demonstrates that behavioural monitoring alone cannot detect when neural state transitions occur, underscoring the need for individualised physiological monitoring within Challenge Point Framework-based rehabilitation systems.

INTRODUCTION

Effort and fatigue are distinct, yet interrelated, measures critical to inform effective motor rehabilitation. Effort refers to active investment of resources to meet task demands. In the cognitive domain, these resources include attentional allocation, working memory engagement, and processing speed. In contrast, fatigue is defined as a time-dependent state characterized by the progressive depletion of resources, resulting in decreased vigilance and processing efficiency. Hockey's compensatory control model provides a mechanistic account of this relationship: performance may be actively maintained under developing fatigue through increased resource expenditure, but only at the cost of elevated subjective effort and physiological strain [1]. Where primary task performance is maintained, decrements may instead manifest as disrupt-

tion to secondary activities, less efficient strategy use, and/or fatigue after-effects (i.e. prolonged recovery, reduced motivation for subsequent tasks, carry-over impairment), emphasizing that effort and fatigue can co-occur and interact dynamically in a variety of ways [1].

Despite the conceptual distinction between effort and fatigue, they are identified by many of the same physiological signals, and can produce overlapping or opposing patterns. While existing literature has attended to the use of physiological signals to identify and measure effort and fatigue, they are often examined in isolation without assessing their relationship, and are defined inconsistently and often times interchangeably, lacking a unified framework.

The Challenge Point Framework (CPF) provides a structured approach for titrating task difficulty and maximizing motor learning, which has been applied to optimize motor rehabilitation [2]. CPF proposes that optimal learning occurs when task demands are aligned with the individual's skill level and task performance, promoting engagement without overwhelming or demoralizing patients. The point at which optimal learning/recovery occurs is referred to as the challenge point. The optimal challenge point shifts as skill improves, or when fatigued. Within the CPF, effort informs whether task difficulty should be increased (e.g., low effort indicating under-challenge), whereas fatigue indicates a functional limit. Beyond these limits, increasing difficulty may elevate risks, reduce learning efficiency, and/or discourage patients.

Physiological signals, such as electroencephalogram (EEG) and eye tracking (ET) (i.e., gaze and pupillometry), have been proposed to objectively measure cognitive effort and/or fatigue. EEG-based metrics of interest in identifying cognitive states include spectral and connectivity features of different brain rhythms. The meta-analysis by Chikhi et al. [3], summarizes that cognitive workload produces frontal θ increase and α decrease, aligning with Klimesch et al.'s review [4] showing frontal θ and parietal α desynchronisation, jointly indicating effortful processing. Arnau et al. [5], found that θ increases during inter-trial intervals reflecting fatigue-related idling of cognitive control networks, whereas stimulus-locked θ decreases over a session reflecting depleted executive resources and reduced task engagement. This dual be-

haviour means that θ alone cannot distinguish compensatory effort from fatigue without considering its temporal and spatial context. On the other hand, α power has been shown to consistently decrease with active engagement and increase with fatigue, specifically over posterior channels [6]. γ oscillations show the opposite profile wherein power increases with cognitive load, working memory maintenance, and feature binding, but decreases with fatigue and time-on-task [7]. Furthermore, Howard et al. [7] demonstrated a near-linear relationship between γ power and Sternberg memory load at frontal and temporal regions, where γ decreases as time-on-task and fatigue increase [6]. This bidirectional profile makes γ a valuable marker for CPF.

EEG electrode-level connectivity analysis has been found useful in characterizing effort and fatigue. Fronto-parietal θ synchrony, quantified via Phase Locking Value (PLV), has been found to serve as a mechanism for long-range communication between cognitive networks, scaling with working memory demand and executive control [8]. Sauseng et al. demonstrated that θ coherence between frontal and parietal sites increases during executive manipulation of visuospatial information, while fatigue reduces network efficiency and diminishes fronto-parietal synchrony over time [9],[10].

Eye-tracking metrics provide access to arousal and cognitive load indicators through the oculomotor system. Pupil dilation, reliably indexed by task-evoked pupil dilation (TEPD), has been found to scale with information-processing load [11]. Gilzenrat et al. confirmed these findings behaviourally, showing increases in baseline pupil diameter accompanying disengagement from task [12]. On the other hand, the Pupil Unrest Index (PUI) quantifies slow spontaneous pupil oscillation validated as a marker of arousal instability, correlating with EEG δ , θ , and alpha-1 power in sleep-deprived adults and predicting subsequent performance failure [13]. Lastly, gaze entropy captures scanning strategy information such that more focused, lower-entropy fixation patterns correspond to effortful engagement, while dispersed high-entropy patterns accompany fatigue-related attentional drift [14],[15].

The primary objective of this preliminary study is to assess the sensitivity of different physiological features in identifying transitions in cognitive states, which may correspond to (cognitive) effort and fatigue, and to compare them to the sensitivity of established behavioural metrics. The secondary objective is to investigate individual variability in the association between physiological and behavioural measures around state transitions. To investigate, this study employed a temporal change-point detection framework to determine whether and when a reliable transition in neurophysiological state occurs within a sustained cognitive task (Attention Network Task), and to characterise the physiological signatures (i.e., EEG, ET) of that transition.

Rather than dividing the task into fixed pre- and post-periods, classifiers were trained at every candidate split

time to find the temporal boundary at which two states are maximally discriminable. This approach makes no assumption about when the transition occurs, quantifies its timing on a per-participant basis, and directly compares the discriminative value of neural and oculomotor signals against overt task performance, providing a data-driven test of the compensatory effort hypothesis within the CPF context. By identifying distinct neural and physiological signatures of adaptive effort versus fatigue, rehabilitation protocols can be made more precise, dynamic, and responsive to the individual's evolving state. For example, if performance decline is driven by cognitive fatigue, task adaptation may involve reducing working memory demands, simplifying instructions, or pacing attentional load. On the other hand, inadequate cognitive effort can be addressed with increasing task difficulty to help with engagement.

MATERIALS AND METHODS

Participants:

Seven healthy adults (19–36 years; 3 female, 4 male) participated. All self-reported no known neurological or musculoskeletal disorders.

Physiological Recording Hardware:

EEG was recorded using a g.Nautilus-16 wireless system (g.tec Medical Engineering, 24-bit, 250 Hz [16]) from Fp1, Fp2, F7, F3, F4, F8, T7, C3, C4, T8, P7, P3, P4, P8, O1, and O2, with ground and reference placed on each of the participant's mastoids. Signals were streamed and synchronised through the Lab Streaming Layer (LSL) [17], and segmented post-hoc. Pupil diameter and gaze position were recorded using Pupil Labs Neon glasses (Pupil Labs, Berlin) [18], synchronised with task events via LSL [17]. Pre-task resting-state baseline (1-min eyes-open and eyes-closed) established the pupil reference mean for task-evoked pupil dilation and the baseline eyelid aperture for PERCLOS calculation.

Tasks:

Participants completed the Attention Network Task (ANT) continuously for 60 minutes. The ANT presents targets flanked by congruent, incongruent, or neutral stimuli, preceded by alerting, spatial, or no-cue conditions, enabling simultaneous assessment of three attentional networks: alerting, orienting, and executive conflict. Reaction time (RT) and accuracy were recorded trial-by-trial. Resting-state baselines were collected immediately before and after the task.

ANALYSIS

Windowing:

A common 30-second non-overlapping window scheme was applied uniformly across all modalities.

Feature Extraction:

Behavioural data were recorded as timestamped trial-level files. Trials with RT below 100 ms were excluded as anticipatory responses. Response measures, such as

mean, median, and standard deviation of RT across all valid trials; overall accuracy; and trial count (reflecting processing speed) were computed per window. Additionally, condition-specific RT and accuracy were calculated separately for each flanker congruency condition (congruent, incongruent, neutral). Lastly, attentional network scores were computed with three difference scores operationalizing the core ANT networks. The alerting score (RT double-cue - RT no-cue) quantifies the benefit of a temporal warning cue. The orienting score (RT spatial-cue - RT double-cue) quantifies the additional benefit of spatial location information. The conflict score (RT incongruent - RT congruent) quantifies the executive cost of flanker interference. Positive values indicate the expected directional benefit or cost for each network.

Eye-tracking gaze and eyelid signals were smoothed with an 11-point Savitzky–Golay filter (polynomial order 2) prior to feature extraction. Where both left and right pupil channels were available, pupil diameter was computed as their mean. The mean pupil diameter, pupil range (max – min, as a proxy for reactivity), pupil variance, Pupil Unrest Index (PUI, computed as the mean absolute rate of change of pupil diameter $|\Delta d / \Delta t|$), and task-evoked pupil dilation (TEPD, mean pupil diameter minus the pre-task baseline mean) were extracted per window. Gaze entropy was computed as the Shannon entropy (bits) of the 2D gaze position histogram over a 25×25 bin grid, quantifying spatial dispersion of fixation. PERCLOS was computed as the proportion of the 30-second window during which the eyelid aperture was classified as closed. A sample was considered closed if the eyelid aperture fell at or below the 15th percentile of the participant’s baseline eyelid distribution, established during the eyes-open baseline period prior to the task. Blink rate was computed as the number of discrete blink events per minute, where a blink was defined as eyelid aperture falling at or below the 10th percentile of the baseline distribution for between 50 and 400 ms.

Sixteen EEG channels were grouped into five regions of interest (ROIs): Frontal (Fp1, Fp2, F7, F3, F4, F8), Central (C3, C4), Temporal (T7, T8), Parietal (P7, P3, P4, P8), and Occipital (O1, O2). EEG signals were bandpass filtered between 0.5 and 45 Hz using a zero-phase FIR filter (Hamming window, firwin design, order = 1650) and a notch filter was applied at 60 Hz to remove power line noise. Following that, artefact removal was performed using the Automatic and Tunable Artefact algorithm [19], with visual inspection of each recording to ensure signal morphology was preserved, and neural components of interest were not over attenuated. Power spectral density was estimated per ROI using a periodogram with a Hann window over 1–45 Hz. Absolute band power was integrated across five canonical bands (δ , θ , α , β , γ), and relative band power was computed by dividing each band by total 1–45 Hz power. Three spectral ratios were additionally derived as cognitive state indices: θ / α , θ / β , and engagement index ($\beta / [\alpha + \theta]$). All features were computed for each of the five ROIs.

Functional connectivity was estimated using directed and undirected approaches applied at the ROI-electrode level (5 ROIs). Signals were detrended prior to connectivity estimation. Multivariate autoregressive modelling (MVAR) was used to estimate directed (partial directed coherence) and undirected (coherence, phase coherence, magnitude squared coherence) connectivity metrics within each 30-second window using a 4th order model fitted via ordinary least squares. Spectral matrices were band-averaged for θ and α . Additional phase-based and amplitude-based connectivity features were computed directly from the filtered EEG data. For phase-based metrics, the analytic signals for the θ and α bands were obtained via the Hilbert transform and phase estimates were derived over 2-second sub-epochs within each 30-second window. Following that, the phase locking value (PLV), weighted phase lag index (wPLI), and imaginary coherence were computed, and for the amplitude-based metrics, z-scored broadband signals using pairwise cross-correlation and autocorrelation-corrected cross-correlation. All connectivity matrices were summarised per window as the mean off-diagonal value.

Modelling:

The primary objective was to identify, for each participant, the time point at which their physiological state changed the most prominently. For each candidate split time t^* , windows were assigned binary labels (class 0: before t^* ; class 1: from t^* onward), and a battery of 7 classifiers was trained and evaluated to determine the effectiveness of discriminating the two classes (i.e., states). The split time maximising classification performance was taken as the best separation point. This was repeated across six feature sets: eye-tracking (8 features), EEG spectral (40 features: 5 relative band powers and 3 spectral ratios across 5 ROIs), EEG connectivity (16 features: 8 MVAR-based, 6 phase-based, and 2 time-domain), combined spectral-connectivity EEG (56 features), all physiological signals (EEG+eye-tracking; 64 features), and behavioural features (14 features).

All classifiers received z-scored features via a `StandardScaler` pipeline. Classifiers supporting `class_weight` were configured with `class_weight='balanced'`, and sample weights inversely proportional to class frequency were passed to `fit()` to equalise class contributions. Split candidates were bounded by a minimum of 20 windows per class (at least 10 minutes per class). Performance was evaluated using 5-fold stratified cross-validation, with probability scores pooled across folds and a single ROC AUC computed from the full pooled vector. The best split time for each participant, feature set, and classifier was defined as the candidate t^* yielding the highest ROC AUC.

RESULTS

Classification Performance Across Feature Sets:

Table 1 summarises mean ROC AUC and complementary metrics at the best-split candidate, averaged across

all 7 participants and 7 classifiers for each of the six feature sets. Multi-modal fusion of EEG spectral, EEG connectivity, and eye-tracking features achieved the highest mean ROC AUC (0.933 ± 0.050), followed by the spectral and connectivity combination (0.914 ± 0.060) and EEG spectral alone (0.894 ± 0.079). Eye-tracking (0.885 ± 0.113) and EEG connectivity (0.836 ± 0.081) provided strong unimodal performance, while the behavioural feature set achieved markedly lower discrimination at near-chance binary separation from overt performance metrics alone.

Table 1: Mean classification performance at the best-split candidate (mean $\pm$ SD across models). Bal. Acc. = balanced accuracy; Spec. = specificity. Bold = highest value per column.

Feature set	ROC AUC	Bal. Acc.	F1	Recall	Spec.
All modalities	0.933 $\pm$ 0.050	0.827 $\pm$ 0.105	0.922	0.930	0.725
Spec + Conn	0.914 $\pm$ 0.060	0.820 $\pm$ 0.088	0.876	0.871	0.769
EEG Spectral	0.894 $\pm$ 0.079	0.799 $\pm$ 0.105	0.857	0.861	0.736
Eye Tracking	0.885 $\pm$ 0.113	0.802 $\pm$ 0.121	0.852	0.840	0.763
EEG Connectivity	0.836 $\pm$ 0.081	0.723 $\pm$ 0.102	0.833	0.833	0.613
Behavioural	0.663 $\pm$ 0.065	0.579 $\pm$ 0.072	0.568	0.587	0.572

Temporal Change-Point Analysis:

Table 2 presents the best split time for each participant. Within participant SD of best split-times across different inputs (EEG-spectral, EEG-connectivity, EEG spectral and connectivity, ET, all physiological, behavioural) ranged from 5.2 minutes (S004) to 15.5 minutes (S003). Notably, the best-performing modality varied across participants. While ET was optimal for S001 and S002, EEG-informed modelling approaches outperformed ET-only for S003, S005, and S007. This cross-participant variability in timing and optimal modality likely reflects that per-participant model selection and feature weighting is optimal compared to the fixed-modality approach. To quantify the correspondence between physiological and behavioural change-point times, Pearson correlation between each participant's mean EEG-based best-split time (averaged across EEG spectral, connectivity, and spectral and connectivity based models) and their mean behavioural best-split time, was computed. The resulting correlation was low and statistically non-significant ($r = 0.34$, $p = 0.453$, $N = 7$).

Table 2: Best split time (t^* , min) and ROC AUC per participant by modality. All mod. = all physiological signals; EEG = best across spectral, connectivity, and spec+conn; Eye = eye-tracking; Beh. = behavioural.

Subj.	All modalities		EEG		Eye		Behavioural	
	t^*	AUC	t^*	AUC	t^*	AUC	t^*	AUC
S001	12.75	0.936	29.75	0.889	12.75	0.955	46.75	0.717
S002	11.75	0.949	15.25	0.902	11.25	0.984	37.75	0.679
S003	12.25	0.937	45.75	0.940	27.75	0.919	17.25	0.706
S004	23.75	1.000	10.25	0.997	23.75	1.000	14.25	0.779
S005	40.75	0.999	41.25	0.999	36.25	0.990	15.25	0.808
S006	12.25	0.920	12.25	0.920	11.25	0.693	28.25	0.667
S007	10.75	0.970	10.75	0.962	31.25	0.892	11.25	0.698

Changes in Physiological Features at the Change-Point:

Feature values were compared between pre- and post-split phases for all seven participants ($N = 7$) using the

all-modality feature matrix. Note that no feature reached statistical significance ($p < 0.05$) at this sample size.

Pupillometric measures increased post-split: mean pupil diameter (+0.102 mm), TEPD (+0.102), pupil range (+0.113), and PUI (+0.101). PERCLOS showed negligible change (+0.004), inconsistent with drowsiness-related eye closure. All pupillometric changes were directionally consistent with increased arousal and processing load [11][13].

θ -based spectral ratios showed consistent post-split changes across all ROIs. θ/α ratio declined most strongly in the temporal ($1.535 \rightarrow 1.296$, $\Delta = -0.239$) and central ($1.466 \rightarrow 1.248$, $\Delta = -0.218$) regions. θ/β ratios showed similar decreases (frontal $\Delta = -0.261$; central $\Delta = -0.228$). The engagement index $\beta/(\alpha + \theta)$ increased across all ROIs (temporal: +0.100; parietal: +0.087). Relative γ power increased across all five ROIs (Temporal +0.027, Central +0.021, Parietal +0.020, Occipital +0.019, Frontal +0.016). These changes are directionally opposite to cognitive fatigue trends reported in literature, which is characterised by rising θ , increasing θ/α ratios, and declining γ [6][20]. Connectivity changes were small and frequency-specific: MVAR-based θ coherence decreased ($\Delta = -0.007$), θ PLV decreased ($\Delta = -0.006$), while alpha wPLI increased (+0.008).

Figure 1 1, illustrates the dynamics for participant S005. All physiological markers show stable trajectories until ≈ 35 –41 min, at which point γ power, engagement index, and pupil diameter change abruptly. EEG-informed models found the best split to be at 41 mins, whereas the behavioural-based classifier identified an optimal split time at 15 mins. The 26-minute gap between physiological and behavioural change-points suggests performance-only monitoring would trigger CFP challenge adjustment well before the physiological-based feature transition. The difference here, and in others in the sample, suggests behavioural features may not correspond to underlying physiological state transition. Instead, behavioural data may be influenced by learning effects, task-adjustment periods, and/or environmental factors. Eye-tracking and EEG-based models exhibited a less drastic difference with eye-tracking splits ≈ 5 minutes preceding the EEG-based split time.

Feature Importance:

Permutation importance computed at each participant's mean optimal split revealed θ PLV as the most discriminative feature overall (mean importance = 0.0057), followed by PUI (0.0050), central γ (0.0037), α PLV (0.0026), and temporal α (0.0023). Eye-tracking features were prominently represented in the top ten, with gaze entropy (0.0019), pupil mean (0.0018), pupil variance (0.0016), and TEPD (0.0013) all ranking in the top fifteen features across participants. Despite a small session-average pre-post difference ($\Delta = -0.006$), the high ranking of θ PLV suggests its discriminative value reflects a phase-coordination transition at the split boundary rather than a sustained shift.

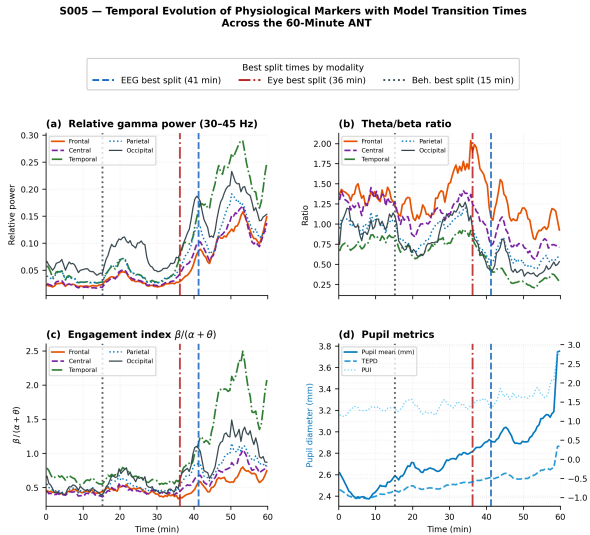


Figure 1: Temporal evolution of key physiological features across the 60-minute ANT for participant S005.

DISCUSSION

Multimodal physiological signals discriminated pre- and post-transition task phases with mean ROC AUC of 0.933, exceeding behavioural features by 0.245 AUC units ($t(6) = 17.89$, $p < 0.001$) across all participants. This is comparable to Trejo et al. [20], who reported 91–100% EEG accuracy when behavioural measures failed to distinguish alertness states for over 30 minutes, and Qi et al. [21], who showed EEG functional connectivity predicted performance impairment ($AUC = 0.89$) when performance indices were non-significant. The low correlation between EEG and behavioural split times ($r = 0.34$, $p = 0.453$) suggests that more than two cognitive states may be present, and that behavioural-informed change points are not directly reflective of internal physiological state changes. Furthermore, results indicate 5 of 7 (excluding S003 and S005) EEG-based change times precedes behavioural-based change points, indicating that some individuals maintain overt performance by mobilising additional cognitive resources, producing earlier physiological change-points with no corresponding behavioural decline, while others show behavioural change before a clear physiological transition.

Post-split spectral changes were directionally inconsistent with hypothesized cognitive fatigue, characterised by rising frontal θ , increasing θ/α ratios, and declining γ [6]. The inverse was observed: decreasing θ/α ratios (temporal $\Delta = -0.239$; central $\Delta = -0.218$; frontal $\Delta = -0.167$), decreasing θ/β ratios (frontal $\Delta = -0.261$; central $\Delta = -0.228$), and increasing γ power across all five ROIs alongside a rising engagement index. Inconsistent with cognitive fatigue, the observed profile is consistent with the compensatory effort framework described by Hockey [1]. Decreasing θ ratios were consistent with Arnau et al. [5], who showed that stimulus-locked θ decreases with time-on-task reflecting depleted trial-by-trial executive resources, even while inter-trial θ rises. The

net spectral pattern at the optimal split time (~ 22 min) is consistent with an early compensatory phase in which β and γ dominate before tonic fatigue-related θ accumulates, in line with Wascher et al. [22], who found compensatory frontal θ increased most in the early-to-middle task phase. Post-split increases in mean pupil diameter ($+0.102$ mm), TEPD ($+0.102$), and pupil range ($+0.113$) are consistent with expected changes in cognitive workload, as it produces enlarged baseline pupil diameter and a shift from exploitative task-optimised engagement toward more diffuse processing [11][13]. Gilzenrat et al. [12] directly confirmed this finding, showing baseline pupil diameter increased as task utility declined. The positive TEPD, specifically indexing effort exertion rather than demand alone, indicates participants were investing more effort relative to their pre-task baseline, consistent with stable ANT performance across the session. Connectivity changes were smaller in magnitude than spectral and pupillometric effects, but showed a frequency-specific pattern inconsistent with uniform fatigue-related reduction. MVAR θ coherence, θ MSC, and θ PLV decreased post-split ($\Delta \approx -0.006$ to -0.007), while alpha wPLI increased ($+0.008$). This divergence between declining θ coupling and increasing α phase-lag mirrors findings from Qi et al. [21] and Sun et al. [23]. The modest post-split θ coherence decline may reflect a reduction in the efficiency of the distributed attentional network necessary for ANT conflict resolution.

Inter-individual variability in change-point timing (13.4 – 35.0 min) and the lack of uniformity in optimal modality across participants (Table 2), emphasizes that a fixed-modality, and fixed-timing monitoring strategy is insufficient. Effective CPF-based rehabilitation requires individualized approaches to determine the physiological features indicative of state changes, and continuous monitoring. Feature importance supports this recommendation with the optimal feature-set differing across participants. These findings argue for passive monitoring frameworks in which modality weights and classifier parameters are continuously updated by individual rather than a universal model.

Limitations:

Limitation include that $N = 7$ with insufficient statistical power for significant pre-post feature testing, thus findings should be treated as hypothesis-generating. The 20-window minimum constraint means that state changes within the first or the last 10 minutes are undetectable. Cognitive states such as boredom and within-session learning were uncontrolled, and the change-point framework assumes a single binary transition, which may oversimplify the continuous and multi-dimension nature of cognitive state change, and no ground truth is available against which the detected transition can be validated.

CONCLUSION

A temporal change-point framework applied to 60-minute ANT recordings from 7 participants demon-

strates that multimodal physiological signals can detect individual neurophysiological state transition with mean ROC AUC of 0.933, exceeding overt behavioural performance features by 0.245 AUC units ($t(6) = 17.89$, $p < 0.001$) in every participant. The grand mean split for physiological based models occurred at 21.6 ± 7.4 minutes, with wide individual variation (range: 13.4–35.0 min). The post-split spectral signature: decreasing θ dominance, increasing γ , engagement index, pupil diameter, TEPD and PUI, is consistent with compensatory effortful processing [1],[5],[6],[11],[13] rather than passive fatigue. θ PLV and Central γ power emerged as the most individually reliable discriminative features. S005 exemplifies how physiological and behavioural change-points can be decoupled, with a 26-minute divergence between the EEG- and behavioural-based split-time identification. The low EEG-behavioural correlation ($r = 0.34$) and high inter-individual variability in change-point timing together establish that group-average or performance-based difficulty adaptation will be systematically mistimed for a substantial proportion of individuals, underscoring the need for continuous, individualised physiological monitoring within CPF-based rehabilitation systems [2]. Stroke patients represent the target population, as physiological monitoring for detecting the effort-to-fatigue transition prior to overt performance declines allows for therapists to adapt task difficulty proactively to ensure efficient learning according to the CPF. The wide inter-individual variability in change-point timing observed here (13.4–35.0 min) will likely be greater in stroke populations, reinforcing the need for individualised rather than group-average monitoring. Validation in patient populations, and assessment of whether EEG and oculomotor markers remain discriminative in the presence of lesion-related signal changes, are critical next steps.

REFERENCES

- [1] G. R. J. Hockey, “Compensatory control in the regulation of human performance under stress and high workload: A cognitive-energetical framework,” *Biol. Psychol.*, vol. 45, no. 1, pp. 73–93, 1997.
- [2] M. A. Guadagnoli and T. D. Lee, “Challenge Point: A Framework for Conceptualizing the Effects of Various Practice Conditions in Motor Learning,” *J. Motor Behav.*, vol. 36, no. 2, pp. 212–224, 2004.
- [3] S. Chikhi, N. Matton, and S. Blanchet, “EEG power spectral measures of cognitive workload: A meta-analysis,” *Psychophysiology*, vol. 59, no. 6, p. e14009, 2022.
- [4] W. Klimesch, “EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis,” *Brain Res. Rev.*, vol. 29, no. 2, pp. 169–195, 1999.
- [5] S. Arnau, T. Brümmer, N. Liegel, and E. Wascher, “Inverse effects of time-on-task in task-related and task-unrelated theta activity,” *Psychophysiology*, vol. 58, no. 6, p. e13805, 2021.
- [6] S. K. L. Lal and A. Craig, “A critical review of the psychophysiology of driver fatigue,” *Biol. Psychol.*, vol. 55, no. 3, pp. 173–194, 2001.
- [7] M. W. Howard et al., “Gamma oscillations correlate with working memory load in humans,” *Cereb. Cortex*, vol. 13, no. 12, pp. 1369–1374, 2003.
- [8] J.-P. Lachaux, E. Rodriguez, J. Martinerie, and F. J. Varela, “Measuring phase synchrony in brain signals,” *Hum. Brain Mapp.*, vol. 8, no. 4, pp. 194–208, 1999.
- [9] P. Sauseng, W. Klimesch, M. Schabus, and M. Doppelmayr, “Fronto-parietal EEG coherence in theta and upper alpha reflect central executive functions of working memory,” *Int. J. Psychophysiol.*, vol. 57, no. 2, pp. 97–103, 2005.
- [10] P. Sauseng, B. Griesmayr, R. Freunberger, and W. Klimesch, “Control mechanisms in working memory: A possible function of EEG theta oscillations,” *Neurosci. Biobehav. Rev.*, vol. 34, no. 7, pp. 1015–1022, 2010.
- [11] P. van der Wel and H. van Steenbergen, “Pupil dilation as an index of effort in cognitive control tasks: A review,” *Psychon. Bull. Rev.*, vol. 25, no. 6, pp. 2005–2015, 2018.
- [12] M. S. Gilzenrat, S. Nieuwenhuis, M. Jepma, and J. D. Cohen, “Pupil diameter tracks changes in control state predicted by the adaptive gain theory of locus coeruleus function,” *Cogn. Affect. Behav. Neurosci.*, vol. 10, no. 2, pp. 252–269, 2010.
- [13] F. Regen, H. Dorn, and H. Danker-Hopfe, “Association between pupillary unrest index and waking EEG activity in sleep-deprived healthy adults,” *Sleep Med.*, vol. 14, no. 9, pp. 902–912, 2013.
- [14] Z. Cui et al., “Gaze transition entropy as a measure of attention allocation in a dynamic workspace involving automation,” *Sci. Rep.*, vol. 14, p. 23405, 2024.
- [15] S. K. Pokkula, A. Amresh, and J. Duval, “Gaze entropy as a measure of player performance and its correlation with focus and attention,” in *Proc. ETRA '25*, New York, NY, USA: ACM, 2025.
- [16] g.tec medical engineering GmbH, “g.Nautilus Research Headset.” [Online]. Available: <https://www.gtec.at/product/gnautilus-research/>
- [17] C. Kothe et al., “The lab streaming layer for synchronized multimodal recording,” *Imaging Neuroscience*, vol. 3, p. IMAG.a.136, Sep. 2025, doi: 10.1162/IMAG.a.136.
- [18] Pupil Labs GmbH, “Neon Eye Tracker.” [Online]. Available: <https://pupil-labs.com/products/neon/>
- [19] N. Bajaj, “ATAR: Automatic and tunable artifact removal algorithm,” in *Signal Processing Toolkit (spkit)*. [Online]. Available: https://spkit.github.io/guide/notebooks/ATAR_Algorithm_EEG_Artifact_Removal.html [Accessed: Apr. 17, 2025]
- [20] L. J. Trejo, K. Kubitz, R. Rosipal, R. L. Kochavi, and L. D. Montgomery, “EEG-based estimation and classification of mental fatigue,” *PSYCH*, vol. 6, no. 5, pp. 572–589, 2015.
- [21] P. Qi et al., “EEG functional connectivity predicts individual behavioural impairment during mental fatigue,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 9, pp. 2080–2089, 2020.
- [22] E. Wascher et al., “Frontal theta activity reflects distinct aspects of mental fatigue,” *Biol. Psychol.*, vol. 96, pp. 57–65, 2014.
- [23] Y. Sun, J. Lim, J. Meng, K. Kwok, N. Thakor, and A. Bez-erianos, “Discriminative analysis of brain functional connectivity patterns for mental fatigue classification,” *Ann. Biomed. Eng.*, vol. 42, no. 10, pp. 2084–2094, 2014.