

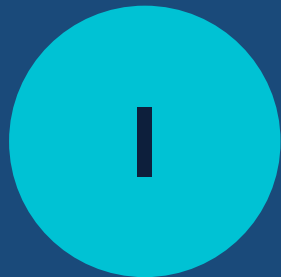
Passive Brain-Computer Interfaces Beyond the Lab: Neurophysiological Models for Safety-Critical Contexts

Neurophysiological signal processing for mental state monitoring

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Outline

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Brain-Computer Interfaces

Concepts, taxonomy, and the passive BCI paradigm

What is a Brain-Computer Interface?

A Brain-Computer Interface (BCI) is a system that establishes a direct communication pathway between the brain and an external device, bypassing conventional neuromuscular output channels.

Sense

Record brain signals (EEG, fMRI, ECoG, fNIRS...)

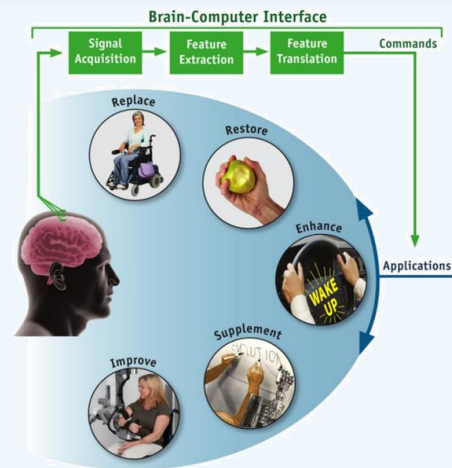
Decode

Extract features & classify mental/cognitive states

Act

Drive feedback, control devices, trigger alerts

Key insight: BCIs do not necessarily require active user intent — the brain continuously produces signals encoding cognitive and emotional states that can be monitored passively in real time.



BCI Taxonomy: Active · Reactive · Passive

Active BCI

User-driven

The user voluntarily modulates brain activity to generate a control signal (e.g., motor imagery, SSVEP, P300 speller). Requires explicit mental effort and training.

Examples:

Assistive technology for paralysis, neuroprosthetics, spelling devices

Reactive BCI

Stimulus-driven

Brain responses to external stimuli (visual, auditory, tactile) are exploited for control. The user reacts but does not need to perform a deliberate mental action.

Examples:

Event-related potential (ERP) paradigms, attention-based control

Passive BCI

State-monitoring

Brain activity is recorded while the user performs natural tasks. No intended control signal — the system monitors mental/cognitive states implicitly in the background.

Examples:

Mental workload, drowsiness, stress, engagement in operational settings

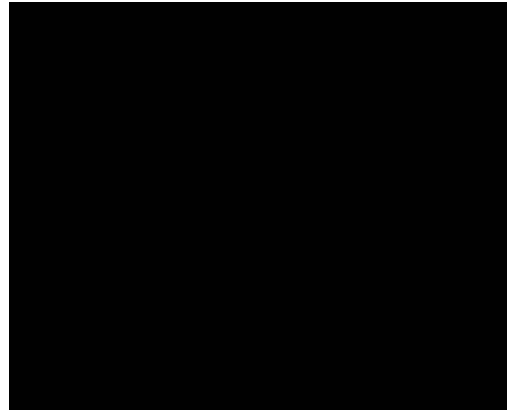
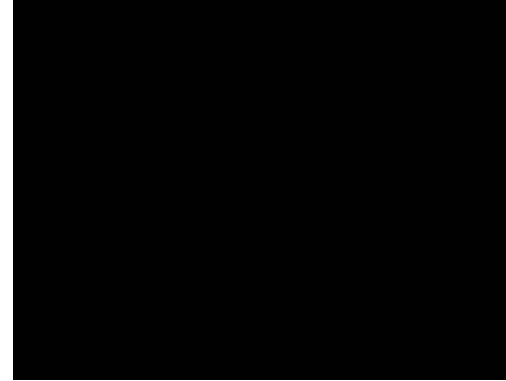
Active BCI (communication & control, restoration, rehab)



SANTA LUCIA
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Why Passive BCIs in Operational Contexts?

Passive BCIs are uniquely suited for real-world monitoring because they do not interfere with the primary task.

1 **Non-intrusive:**

Users perform their normal activities; no explicit mental effort or protocol compliance required.

2 **Continuous monitoring:**

Real-time, uninterrupted assessment of cognitive and affective states over extended periods.

3 **Implicit state detection:**

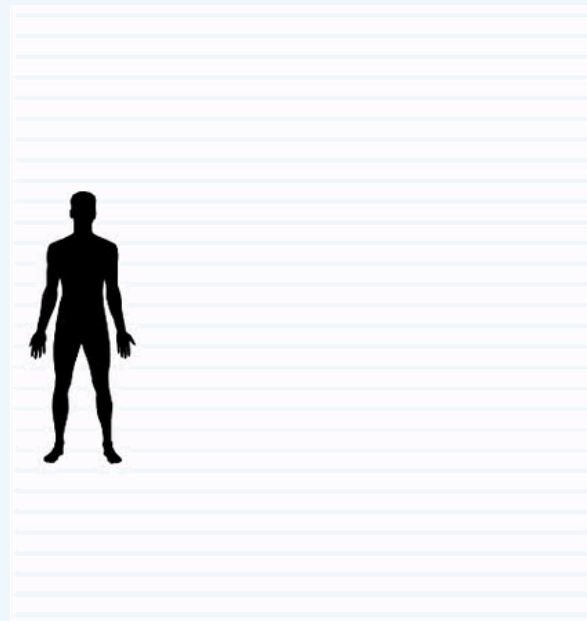
Mental states (workload, fatigue, stress) are encoded in brain signals without voluntary control.

4 **Safety-critical applications:**

Enable proactive alerts and adaptive systems in aviation, road transport, surgery, ATC, and more.

5 **Multimodal integration:**

Easily combined with peripheral signals (EOG, ECG, EDA, PPG) for robust state assessment.



Neurophysiological Signals in Passive BCIs

EEG

Electroencephalography

Cortical electrical activity. Gold standard for passive BCIs: ms-level temporal resolution, rich cognitive state information in α , θ , β bands.

EOG

Electrooculography

Eye movement and blink activity. Extracted from EEG frontopolar channels. Eye blink rate (EBR) correlates with drowsiness and cognitive load.

ECG/HR

Electrocardiography / Heart Rate

Cardiac autonomic activity. HR and HRV reflect stress, mental effort, and arousal level. Derivable from ECG or PPG sensors.

EDA

Electrodermal Activity

Skin conductance reflects sympathetic arousal. Sensitive to emotional states, stress, and high-stakes events.

fNIRS

Functional Near-Infrared

Spectroscopy

Haemodynamic response (oxyHb/deoxyHb). Robust to movement, useful in ecological settings where EEG is challenging.

Human Factors: What and Why?

Mental Workload

Amount of cognitive capacity required to perform a task. Direct impact on performance in operational contexts.

Stress

Physiological response to mental/emotional/physical demands. Linked to the balance between environmental demands and available resources.

Mental Drowsiness & Fatigue

Progressive decrease in reaction time, impaired information processing, memory errors, and reduced vigilance.

Cooperation and Teamwork

Inter-brain dynamics to evaluate how two or more humans are cooperating in high-risk environments.

→ *The U-inverted Yerkes-Dodson curve describes the relationship between cognitive arousal and performance.*

Why Human Factors Are So Crucial



1.2M+

deaths per year
on the roads
worldwide

*Human error: cause in 57% of
accidents, contributing factor
in >90%*

>70%

of aviation accidents
due to human error

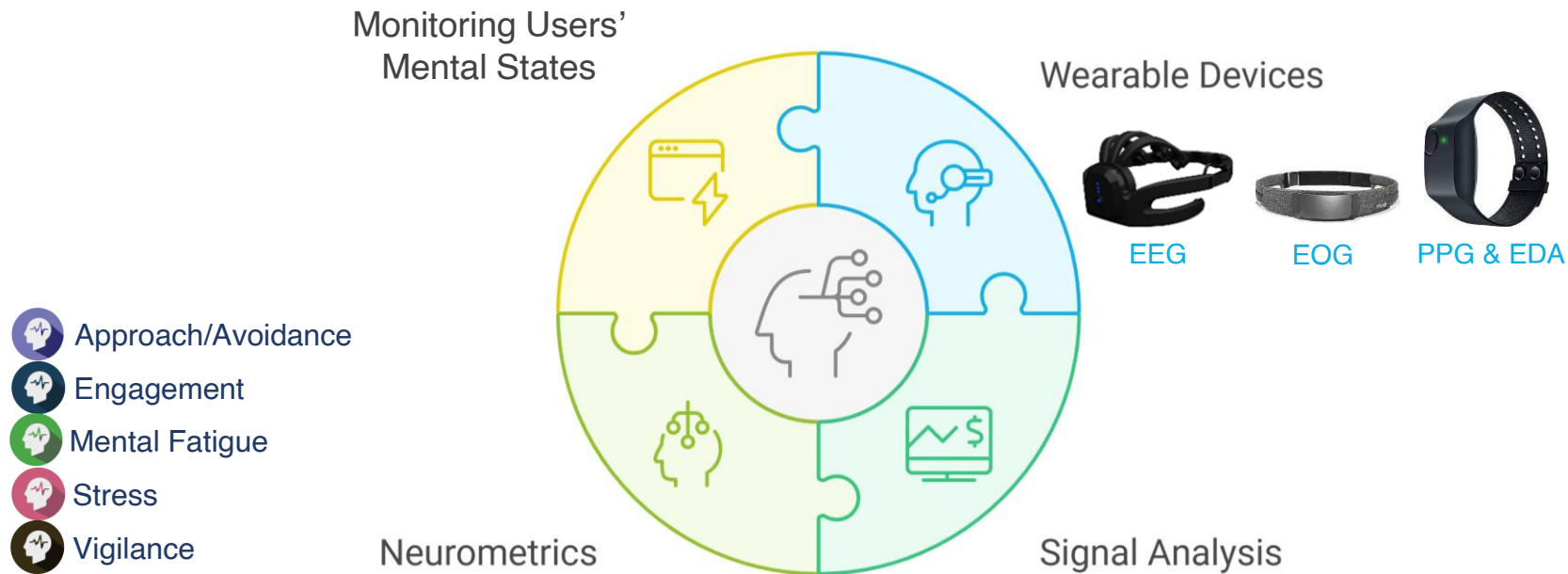
*Most caused by mental
overload of pilots or
deterioration of cognitive
performance*



The Human Factor is the most important — but least controllable — element in operational environments.

Passive BCIs offer a non-intrusive, continuous, and objective tool for monitoring it.

Our Research Approach



Mindtooth Touch EEG system



A project funded by EU H2020 - FTI GA 950998

<https://mindtooth-eeg.com/>



1

Case Study – o-CLEAN Method

Online EEG ocular artifact removal via Multi-channel Wiener Filter

o-CLEAN: a novel multi-stage algorithm for the ocular artifacts' correction from EEG data in out-of-the-lab applications. Vincenzo Ronca et al 2024 J. Neural Eng. 21 056023

EEG Signal Analysis: The Ocular Artifact Problem

1

Ocular Interference

EEG signals are heavily contaminated by electrical activity from eye movements and blinks — collectively termed ocular artifacts.

2

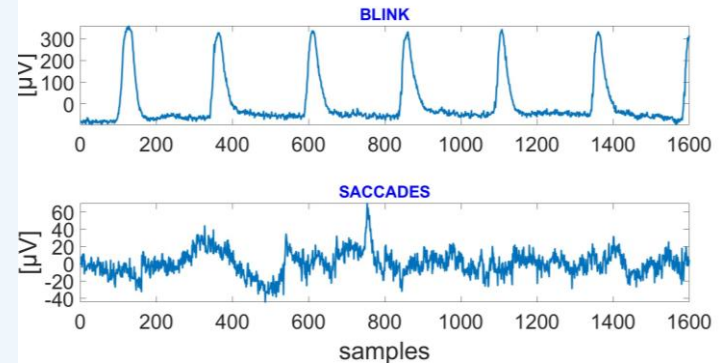
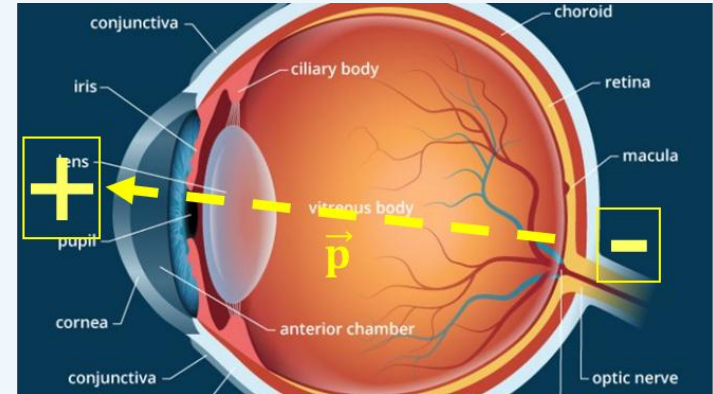
Data Integrity at Risk

Blink-related potentials can be 10× larger than cortical EEG signals, distorting the underlying brain activity and leading to inaccurate interpretation.

3

Analysis Challenges

Effective ocular artifact removal is a prerequisite for reliable EEG-based research and clinical/operational applications, especially in real-time settings.



Overview of Existing Techniques for Artifact Removal

1. Manual Rejection

Visually identifying and removing contaminated EEG segments. Time-consuming, subjective, and incompatible with online/real-time use.

Limitation: Not scalable

2. Regression-based Methods

Using the correlation between EEG and EOG signals to subtract ocular artifacts. Examples: Gratton & Coles method.

Limitation: Assumes linearity

3. Blind Source Separation (BSS)

Techniques like ICA (Independent Component Analysis) separate artifact sources from brain activity. AMICA is a state-of-the-art ICA variant.

Limitation: High computational cost

o-CLEAN: EEG Artifact Removal via Multi-channel Wiener Filter (MWF)

The o-CLEAN method implements an online (real-time compatible) pipeline based on the Multi-channel Wiener Filter:

1

Ocular Artifact Detection

Blink components are identified in a short calibration dataset using principal component analysis of the EOG signal.

2

Filter Training

The MWF models the relationship between the neural EEG signal and the ocular artifact (blinks), generating an optimal estimate of the 'clean' EEG.

3

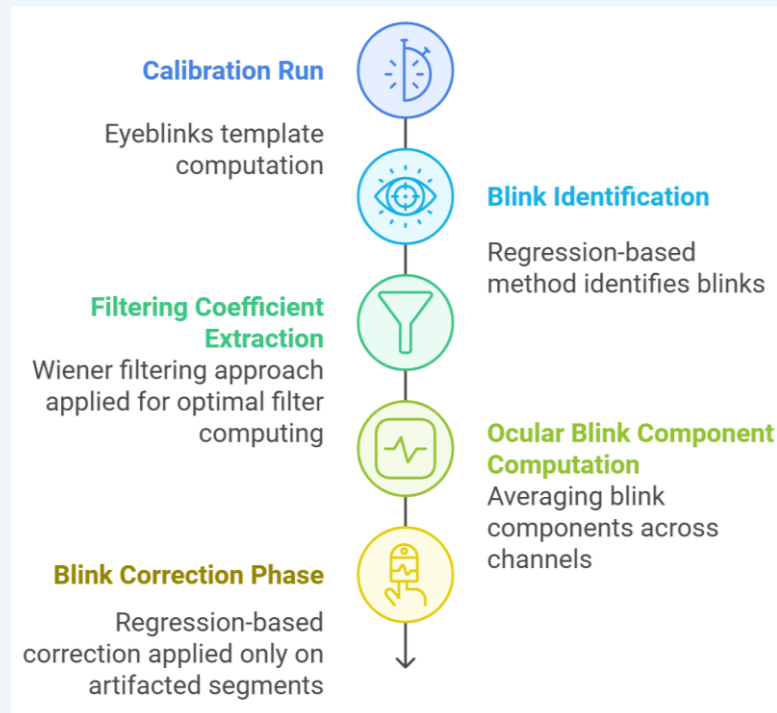
Application on EEG Dataset

The trained filter is applied to new EEG recordings — enabling real-time use on continuous data streams.

4

Artifact Correction

Subtraction is weighted by the channel-specific degree of correlation with the blink artifact, minimising distortion of genuine neural activity.



Methodology of the Comparative Study

Benchmark Datasets

Two datasets were used:

- Controlled laboratory dataset
- Real environment dataset (real driving conditions)

Publicly available EEG datasets with known ocular artifacts.

Competing Methods

- Gratton & Coles (regression)
- AMICA (ICA-based)
- MWF (Wiener filter)
- Reblinca (regression)
- Sgeyesub (BSS-based)

Evaluation Metrics

- Mutual Information (EOG vs. EEGcorr / non-corr)
- Pearson Correlation (EOG vs. EEGcorr / non-corr)
- Frequency Correlation
- PSD preservation (no blink vs. blink segments)
- Signal-to-Noise Ratio (SNR)

Statistical Analysis

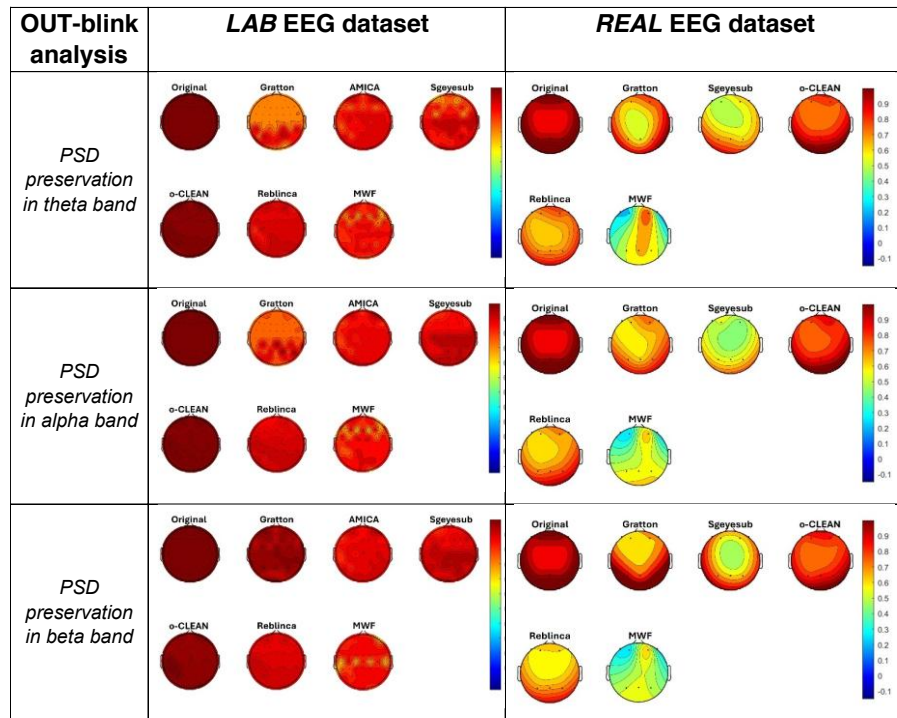
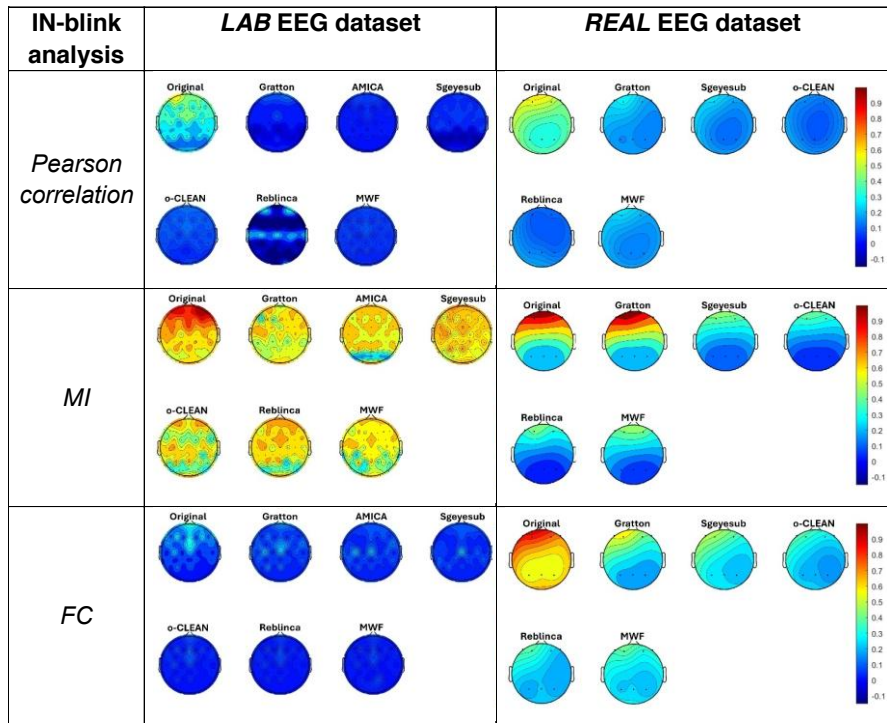
Rigorous statistical testing to ensure:

- Robustness of results across datasets
- Generalisability of findings
- Significance of improvements over baselines

Comparative analysis between controlled and real-world EEG conditions.

Results: Efficiency & Specificity Assessment

The o-CLEAN method was evaluated on both controlled and real driving datasets against state-of-the-art alternatives.



Results: Efficiency & Specificity Assessment

The o-CLEAN method was evaluated on both controlled and real driving datasets against state-of-the-art alternatives.

Efficiency (Artifact Removal)

- ✓ Significantly reduced mutual information between EOG and corrected EEG
- ✓ Outperformed Gratton & Coles and AMICA in most metrics
- ✓ Superior SNR improvement across both controlled and real datasets

Specificity (Neural Preservation)

- ✓ PSD preservation: neural spectral content preserved post-correction
- ✓ Minimal distortion to non-artifact EEG epochs
- ✓ Better balance between artifact removal and signal preservation vs. competitors

Real-World Compatibility

- ✓ Computationally efficient: suitable for online/real-time processing
- ✓ Tested on ecological driving data — not only lab conditions
- ✓ No requirement for manual ICA component selection



2

Case Study – MDrow Index

EEG-based mental drowsiness detection for driving safety

Di Flumeri G., Ronca V. et al. (2022). EEG-Based Index for Timely Detecting User's Drowsiness Occurrence in Automotive Applications. Front. Human Neuroscience. doi: 10.3389/FNHUM.2022.866118

The Drowsiness Problem in Road Safety

In road safety there is still a lack of a synthetic, real-time-compatible index able to evaluate driving drowsiness from the driver's brain activity.

The Challenge

- Drowsiness develops gradually and is self-underestimated
- Behavioral measures (lane deviation, RT) are lagging indicators
- Existing autonomic indices (HR, EBR) lack temporal resolution
- Most EEG approaches require offline analysis or parietal sensors

Our Objective

- Develop an innovative EEG-based Mental Drowsiness (MDrow) index
- Compatible with real-time/online detection
- Validated against autonomic indices (EBR, HR)
- Compatible with wearable sensors (frontal channels)

Reference

Di Flumeri G., Ronca V. et al. (2022). EEG-Based Index for Timely Detecting User's Drowsiness Occurrence in Automotive Applications. Front. Human Neuroscience. doi: 10.3389/FNHUM.2022.866118

Experimental Protocol: Simulated Driving

19 participants | 4 driving conditions designed to progressively modulate drowsiness:

WUP

Warm-Up

Baseline driving — alert,
engaged

PERFO

Performance

High-demand driving task

TAV

Tunnel / Boring

Monotonous stretch —
drowsiness onset

DROW

Drowsiness

Specifically designed to
induce drowsiness

Neurophysiological Measurements

- EEG (61 channels) — band-pass 2–40 Hz, ICA artifact removal
- Eye Blink Rate (EBR) from EEG Fpz channel (Reblinca method)
- Heart Rate (HR) from ECG — Pan-Tompkins algorithm
- EEG Global Field Power (GFP) in Alpha band

Behavioural Measurements

- NASA-TLX: subjective workload ratings
- Driving errors: number of incidents per condition
- Used to validate the experimental design (manipulation check)
- Significant decreases in errors during DROW (all $p < 0.01$)

Neurophysiological Parameters & MDrow Rationale

EBR

Eye Blink
Rate

Eye Blink Rate

Autonomic parameter extracted from EEG frontopolar (Fpz) channels. EBR is directly related to mental drowsiness: blink rate increases as alertness decreases.

HR

Heart Rate

Heart Rate

Autonomic cardiac parameter derived from ECG using the Pan-Tompkins QRS detection algorithm. HR and HRV decrease during drowsy states.

MDrow

EEG-based
Drowsiness
Index

EEG-based Drowsiness Index

Derived from EEG Global Field Power in the Alpha band. Alpha spindles (0.5–2 s bursts of high-frequency Alpha) are biomarkers of drowsiness. MDrow combines amplitude, frequency, and rate of Alpha spindles into a single composite index.

MDrow Index Development

Step 1 — Topographic analysis: parietal channels were identified as the primary cortical region showing Alpha synchronisation during drowsy states.

Alpha-OE Ratio

The OE (Eyes Open) condition is the resting state where Alpha is maximal. The ratio Alpha / Alpha_OE is computed to normalise inter-subject variability.

→ Median and skewness of this ratio are significantly higher during DROW ($p < 0.05$).

Threshold Definition

A threshold is computed along the WUP condition to detect peaks (Alpha spindles) above baseline.

Peaks above threshold = putative drowsiness events.

MDrow Index Definition

$$\text{MDrow}(t) = (\text{Alpha_GFP}(t) / \text{Alpha_OE}) \circledast \text{rect}_{30}(t)$$

Convolution of the Alpha–OE ratio above threshold with a 30-second rectangular window → smoothed, temporally stable index, compatible with online implementation.

Results: MDrow vs. EBR vs. HR

Statistical comparison across experimental conditions (PERFO, TAV, DROW):

MDrow

Significantly higher during DROW vs. all other conditions (all $p < 0.01$). Non-zero in >50% of DROW segments vs. <12% in TAV/PERFO. Sensitive to Alpha spindles — increases precisely when synchronisation events occur.

BEST

EBR

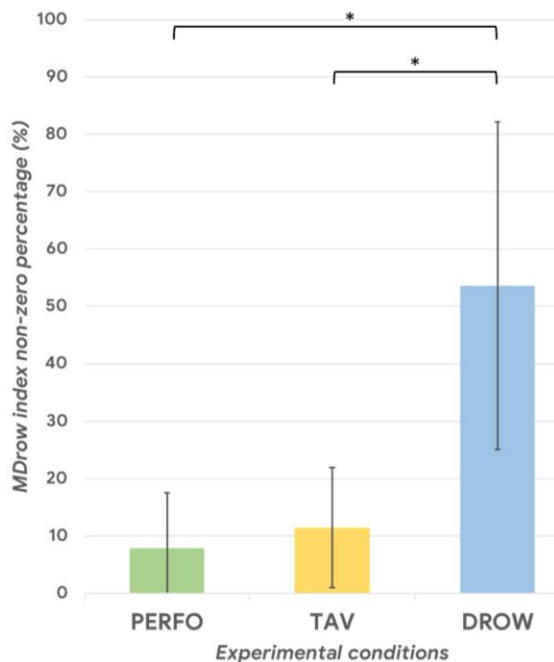
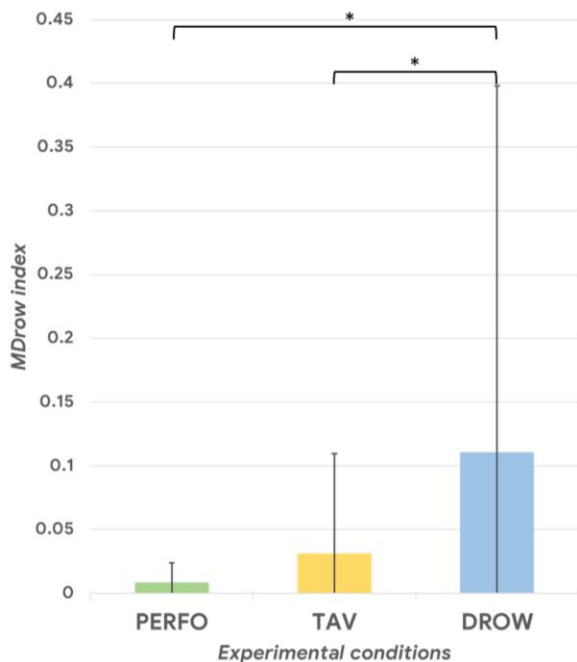
EBR' significantly higher during DROW vs. WUP, PERFO, TAV ($p = 0.03$). Sensitive but lower temporal resolution than MDrow. Detects sustained drowsiness but misses short-term episodes.

HR

HR and HRV significantly decreased during DROW vs. PERFO (HR: $p = 0.02$; HRV: $p = 0.01$). Autonomic signal — slower response time, lower specificity for drowsiness episodes.

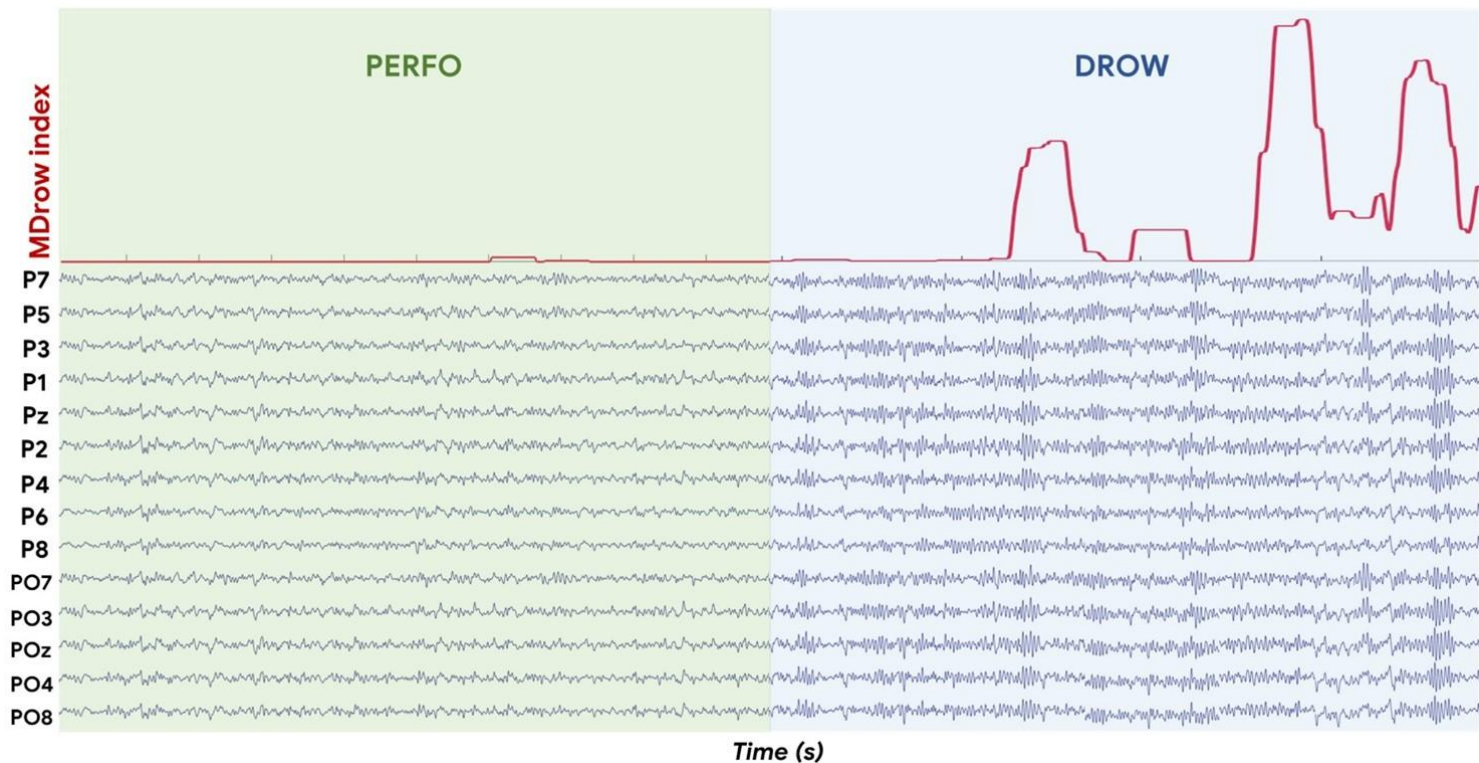
Results: MDrow index

Statistical comparison across experimental conditions (PERFO, TAV, DROW):



- The MDrow index was **significantly higher** during the DROW condition (all $p < 0.01$).
- The MDrow index was higher than zero in more than **50% during the DROW** condition, while its non-zero percentage was lower than **12% during the TAV and PERFO** conditions.

Results: MDrow index



The MDrow index is sensitive in recognizing the **alpha spindles**, in fact it increases while alpha spindles (i.e., synchronization phenomena) occur.

Conclusions: MDrow Index



Reliability confirmed

MDrow reliably detected mental drowsiness while driving — significantly differentiating the DROW condition from all others.



Superior sensitivity

MDrow outperformed both EBR and HR in timely detection of short-term drowsiness episodes (Alpha spindle level).



Online-compatible algorithm

Convolution with a rectangular window makes MDrow directly suitable for real-time/online implementation in automotive systems.



Frontal extension

Subsequent work validated MDrow using frontal EEG channels — compatible with current wearable EEG headsets; impact of electrode reduction also investigated.

Future: application to professional truck drivers in naturalistic settings; full compatibility with wearable EEG headsets (frontal band).



3

Case Study – Teamwork Assessment

Mutual information-based EEG teamwork index in real surgical settings

From Individual Monitoring to Team Assessment

Passive BCIs can be extended beyond individual monitoring — capturing the shared neurophysiological dynamics of cooperating teams.

Cooperation Model

Cooperation is affected by cognitive and emotional alterations in subjects sharing intentions:

- Emotions affect decision-making and cooperative choices
- Physiological compliance of autonomic signals predicts team performance
- Mental state of each team member is NOT independent — it is modulated by the state of co-workers

Measured via EEG: Affective State + Mental State for each subject.

Why Surgery?

Surgery is an ideal high-stakes operational environment:

- Clear teamwork structure (surgeon + assistant + scrub nurse)
- Measurable outcomes (surgery time, patient outcome)
- Expert vs. Novice teams allow skill-level comparison
- Real neurophysiological data collection possible
- Expert/novice differences reflect qualitative cooperation differences

Cooperation Computation: Mutual Information Framework

Cooperation is quantified by the shared information content between the neurophysiological states of co-workers.

MI Approach – MICI

Mutual Information (KNN-based Kraskov estimator):

$$I(X;Y) = \sum p(i,j) \cdot \log [p(i,j) / (p_x(i) \cdot p_y(j))]$$

Input features:

$$W(t) = \frac{GFP\theta(AF3, AFz, AF4)}{GFP\alpha(P3, Pz, P4)}$$

$$AW(t) = GFP\alpha (AF3) - GFP\alpha (AF4)$$

Ccor Approach – CCI

Circular correlation between phase signals:

$$Ccor_{\vartheta, \varphi} = \frac{\sum_{k=0}^{N-1} \sin(\vartheta k - \bar{\vartheta}) \sin(\varphi k - \bar{\varphi})}{\sqrt{\sum_{k=0}^{N-1} \sin^2(\vartheta k - \bar{\vartheta}) \sin^2(\varphi k - \bar{\varphi})}}$$

Input: Signal phase $\vartheta[k]$

Captures non-linear phase synchrony between subjects

Why Mutual Information?

Mutual information is an enhancement of the Pearson correlation coefficient: it captures not only linear relationships but the maximum information shared between variables (Kraskov et al., 2004). Cooperation and Teamwork require characterising the complex, non-linear dynamics of joint mental states — MI is better suited than correlation for this purpose.

Analytic Teamwork Index: From Dyadic to Team Level

Cooperation (2 subjects)

- ▶ Pairwise mutual information: MICI
- ▶ Pairwise circular correlation: CCI
- ▶ Well-validated in the literature
- ▶ Extension to real environments still limited

Teamwork ($N \geq 3$ subjects)

- ▶ $\eta = \text{mean}(\text{CCI-matrix})$ [Ccor approach]
- ▶ $\eta = 1 + \sum \lambda_m \log \lambda_m / \log(K)$ [MI approach]
- ▶ λ_m = normalised eigenvectors of $K \times K$ cross-correlation matrix
- ▶ Novel formulation for real-world use

Validation (Surgeons)

- ▶ 4 Expert teams + 4 Novice teams
- ▶ Real surgeries at Policlinico Umberto I
- ▶ Preliminary extension to 4-subject teams
- ▶ Multimodal: EEG + subjective + behavioural

Experimental Protocol: Real Surgical Teamwork

Study Design

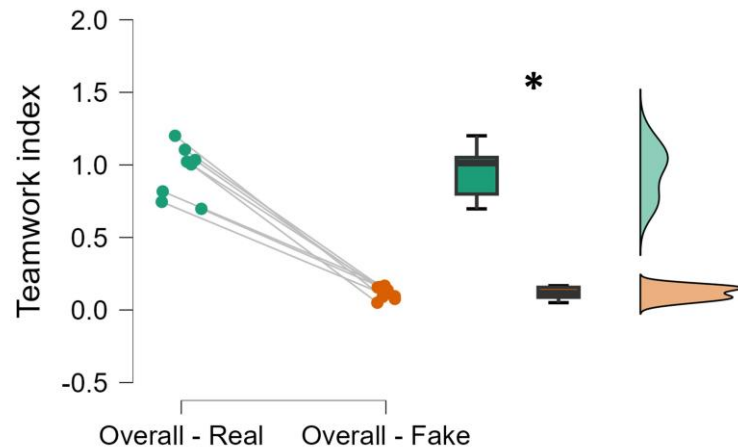
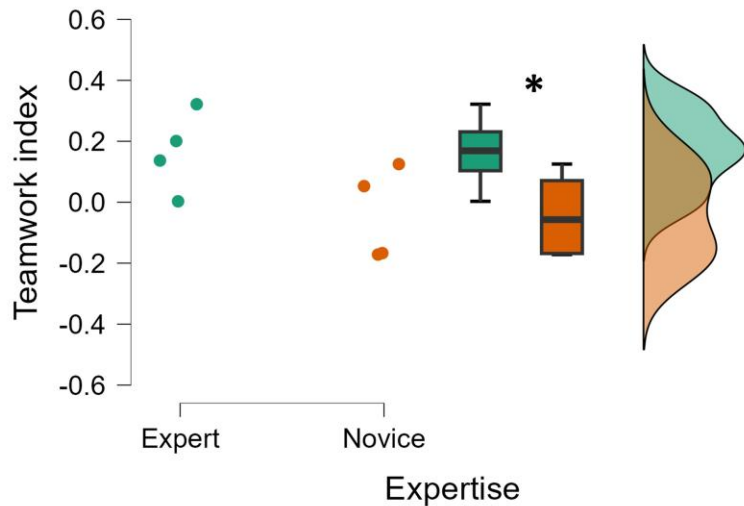
- Cooperation among surgeons during real laparoscopic surgery
- Conducted at Policlinico Umberto I, Rome
- 4 Expert surgical teams + 4 Novice surgical teams
- Preliminary extension of MI model to 4-subject teams
- Real-time EEG recording during actual procedures

Multimodal Data Collection

- Neurophysiological: EEG (mental state + affective state)
- Subjective (SME): workload ratings, SAM questionnaire, collaboration evaluation
- Behavioural: surgery duration, SME performance scores, patient outcome
- Patient: pain level, mental discomfort, physical discomfort (cPDIS)



Results: EEG-based Teamwork Index



Validation — Real vs. Fake: Shuffling each member's data with all others showed that the observed teamwork MI is significantly higher than chance, confirming that team-level neural synchrony is a genuine signal and not a statistical artefact.

Results: EEG-based Teamwork Index vs. Ground-truth Measures

The EEG-based Teamwork Index (mutual information between team members' mental states) was correlated with independent ground-truth measures of team performance.

vs. CBTI (Behavioural)

$$R = 0.68$$
$$p = 0.002$$

Strong positive correlation between EEG Teamwork Index and the Combined Behavioural Teamwork Index (surgery time, SME scores, patient outcome). Expert teams showed higher teamwork indices than novice teams.

vs. cSME (Subjective)

$$R = 0.62$$
$$p = 0.0001$$

Significant correlation with the Combined SME Index (subjective workload + collaboration ratings + SAM questionnaire). Neurophysiological teamwork captures what experts subjectively report about their cooperation quality.

Validation — Real vs. Fake: Shuffling each member's data with all others showed that the observed teamwork MI is significantly higher than chance, confirming that team-level neural synchrony is a genuine signal and not a statistical artefact.

Conclusions: Teamwork Assessment



Multimodal superiority

A multimodal approach (neurophysiological + subjective + behavioural) overcomes the limitations of single-modality assessments, providing a more accurate and comprehensive characterisation of team performance.



EEG as a teamwork sensor

Mutual information between EEG-derived mental states of cooperating individuals is a valid proxy for teamwork quality. Expert teams show significantly higher MI than novice teams.



Real-world applicability

Data collected during actual surgeries — not simulations — demonstrates the ecological validity of passive BCI approaches for high-stakes operational environments.



Scalability to N subjects

The teamwork index formulation extends beyond dyadic (2-person) cooperation to N-member teams, using eigenvector decomposition of the cross-correlation matrix.

4

Case Study – Cognitive Training Index

EEG-based PCA composite for objective training evaluation & VR vs. Physical comparison

Motivation: Evaluating Training Goes Beyond Behaviour

Execution time and error counts do not capture the internal cognitive reorganisation that defines true skill acquisition.

Problem

- Behavioural metrics (time, errors) capture observable output but not neurocognitive dynamics
- Subjective measures (NASA-TLX) suffer from recall bias and low temporal resolution
- VR training is increasing: is cognitive adaptation comparable to physical training?

Approach

- Record wearable EEG (8 channels) during a realistic confined-space industrial maintenance task
- Compute 6 EEG neurometrics (workload, effort, vigilance, attention, stress, motivation)
- Apply PCA to extract the dominant shared component → Cognitive Training Index (CTI)

Objectives

1. Develop & validate CTI as an objective neurophysiological marker of training progression
 2. Compare VR-based training with Physical training using CTI as a modality-independent index
- N=29 participants (Physical n=15 / VR n=14)

Experimental Task: Confined-Space Industrial Maintenance

Realistic confined-space maintenance procedure, designed with INAIL (Italian National Institute for Accident Prevention).

3 operational segments per trial:

① Entrance (~4 min)

Lockout / tagout safety procedures, valve and switch isolation — cognitively demanding, procedurally structured

② Rolling Shutter (~1 min)

Walk + open shutter to access workspace — minimal decision-making, low cognitive load

③ Pipe Replacement (~4 min)

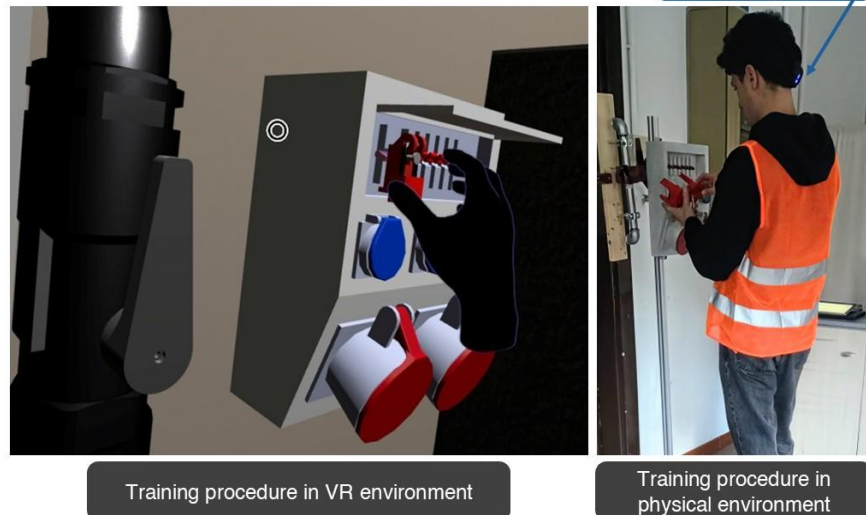
Identify, remove and replace steam-pipe section — step-by-step precision, sustained attention

3 consecutive trials per participant (~9 min each)

Physical group: all 3 trials in real environment

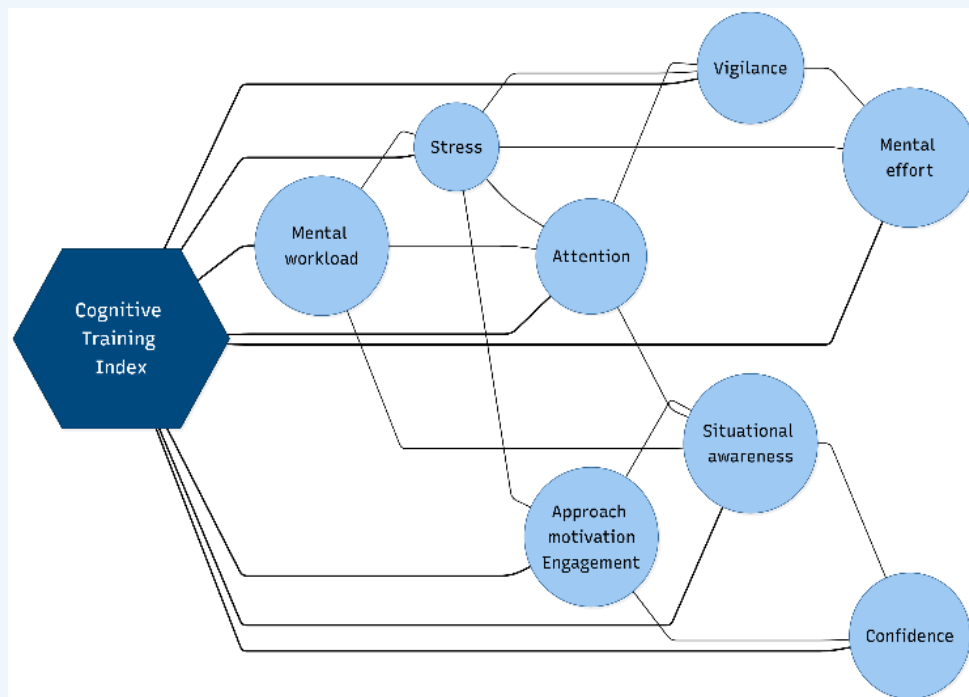
VR group: Trials 1–2 in VR, Trial 3 in real environment

Fig. 2 — VR (left) and Physical (right) environments



Wearable EEG: Mindtooth Touch (8 ch, frontal + parietal), 250 Hz, water-based electrodes — fully compatible with task execution in both environments.

Six EEG Neurometrics: Capturing the Multidimensional Nature of Training



All neurometrics were z-score normalized within each participant across the entire session to remove inter-individual amplitude differences and focus on relative task-related modulations.

All neurometrics computed via Global Field Power (GFP) in individualized IAF-based frequency bands, in 1-s sliding windows.

Mental Workload

$GFP_{\theta}(\text{frontal}) / GFP_{\alpha}(\text{parietal})$

Mental Effort

$GFP_{\theta}(\text{frontal})$

Vigilance

$GFP_{\beta}(\text{frontal})$

Attentional Engagement

$GFP_{\beta}(\text{frontal}) / GFP_{\theta}(\text{frontal})$

Physiological Stress

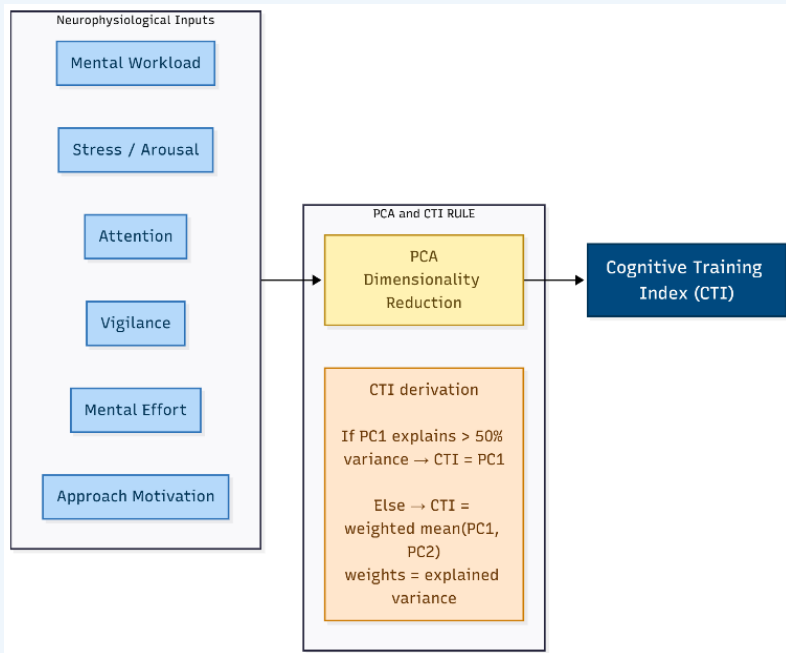
$GFP_{\text{high-}\beta}(\text{parietal})$

Approach Motivation

$GFP_{\alpha}(\text{AF3}) - GFP_{\alpha}(\text{AF4})$ [frontal asymmetry]

PCA-based Cognitive Training Index (CTI): Computation

PCA is applied to the 6-neurometric matrix to extract the dominant shared axis of covariation → CTI = PC1 (if PC1 explains $\geq 50\%$ variance, else weighted PC1+PC2).



Dominant component

PC1 exceeded 50% explained variance for ALL participants → CTI = PC1 alone for all analyses

Stable loading pattern

Bootstrap (B=1000) sign-agreement: 94–98%. LOSO cosine similarity: median=0.94 (IQR 0.92–0.96)

Multivariate — not a proxy

Largest loading: ~23–29% of L1-norm. No single neurometric dominates the PC1 structure

Surrogate validation

Phase-randomized surrogates confirm CTI reflects genuine coordinated neurometric dynamics, not spectral artefacts

Behavioural & Subjective Outcomes: Both Groups Improve

Mixed ANOVA (Trial $\times$ Group): significant main effect of Trial across all measures; Group $\times$ Trial interaction non-significant.

Execution Time

$F = 14.82$
 $p < .001$
 $\eta^2p = 0.35$

Both groups reduced completion time across trials. Rate of improvement did not differ significantly between Physical and VR groups.

Procedural Errors

$F = 10.31$
 $p < .001$
 $\eta^2p = 0.27$

Both groups showed significant error reduction. Physical group improved mainly T1 $\rightarrow$ T2; VR group showed larger gains T2 $\rightarrow$ T3 (transfer to real environment).

NASA-TLX (Workload)

$F = 11.94$
 $p < .001$
 $\eta^2p = 0.30$

Perceived workload decreased progressively across trials. No significant group difference in the final physical trial — VR participants felt equally at ease.

CTI Dynamics in the Physical Group: Phase-Selective Learning

1

Significant CTI increase across trials

$F = 19.04$, $p < .001$, $\eta^2p = 0.42$ — CTI captured progressive neurocognitive reconfiguration during physical training.

2

Cognitively demanding phases

Entrance: $F = 14.05$, $p < .001$

Pipe Replacement: $F = 15.24$, $p < .001$

→ Strong CTI modulation in procedurally complex phases.

3

Low-demand phase: no modulation

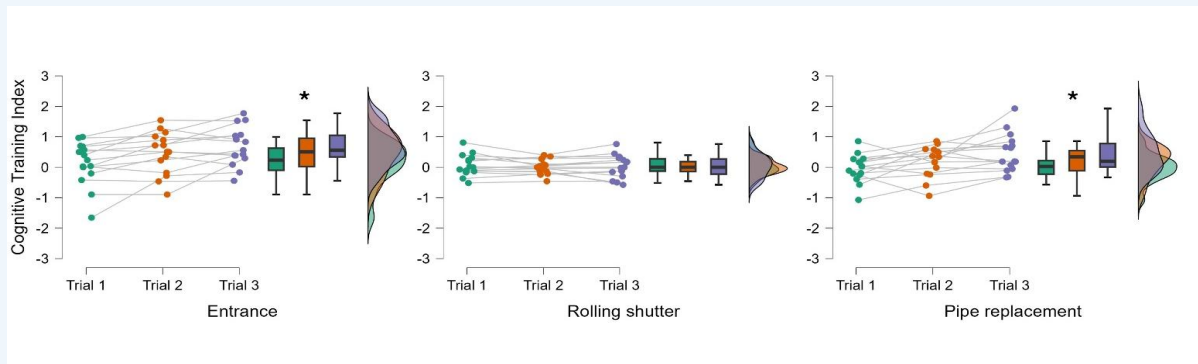
Rolling Shutter: $F = 0.91$, $p = .40$ — CTI remained flat, confirming phase selectivity (not a global amplitude artefact).

4

Surrogate validation

Real CTI $\gg$ surrogate values in Entrance ($d=1.13$) and Pipe Replacement ($d=1.28$).

Rolling Shutter and baseline: indistinguishable from null.



CTI–Behaviour & CTI–Workload Associations

Repeated-measures correlation across both Physical and VR groups:

CTI ↔ Errors

$r = -0.46$ | $p < .001$

Higher CTI → fewer procedural errors. Stronger neurocognitive integration → more accurate execution of safety-critical sequence.

CTI ↔ NASA-TLX

$r = -0.41$ | $p = .001$

Higher CTI → lower perceived workload. CTI tracks cognitive efficiency, not mere neural activation.

CTI ↔ Execution Time

$r = 0.18$ | $p = .12$ (n.s.)

No significant relationship. CTI is not driven by how fast participants complete the task — motor/biomechanical factors operate independently.

→ consistent pattern across training modalities

VR vs. Physical Training: Comparable Neurocognitive Adaptation

Main CTI findings (Physical vs. VR)

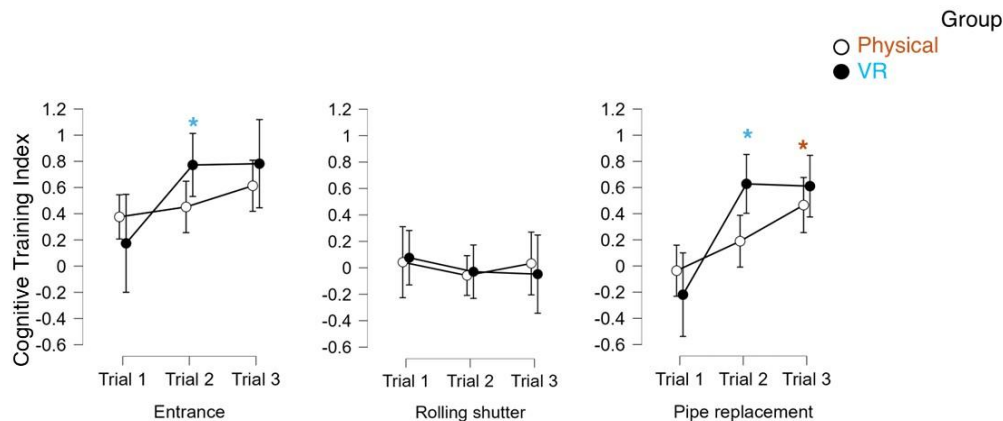
Main effect Trial: $F = 18.21$, $p < .001$, $\eta^2p = 0.39$
Group $\times$ Trial interaction: $F = 1.11$, $p = .34$ (n.s.)

→ Both groups show progressive CTI increase
→ Trajectory of cognitive adaptation statistically equivalent

In the final physical trial: CTI did not differ between groups — VR training brought participants to the same multivariate neurometric profile as physical training.

Interpretation

Lower VR CTI at Trial 1 reflects initial interface novelty cost. Progressive increase in Trials 2–3 consistent with cognitive adaptation once VR interaction becomes fluent. Convergence in Trial 3 supports transfer of cognitive adaptation from VR to the real environment.



Conclusions: Cognitive Training Index (CTI)



A validated, multivariate EEG training index

CTI integrates 6 neurometrics via PCA into a single, psychologically grounded measure that is more sensitive and specific than any individual neurometric alone.



Phase selectivity confirms specificity

CTI increases selectively in cognitively demanding phases (Entrance, Pipe Replacement) and remains at baseline in the low-load Rolling Shutter phase — validated by surrogate analysis.



Links to meaningful outcomes

CTI correlates negatively with procedural errors ($r=-0.46$) and perceived workload ($r=-0.41$), not with execution time — it tracks cognitive quality, not motor speed.



VR training is neurophysiologically equivalent

The CTI trajectory in VR-trained participants matches that of physically trained participants, supporting VR as a viable, safe and cost-effective training modality for confined-space operations.



Towards adaptive training systems

CTI is computed from wearable EEG using sliding windows and a linear pipeline → compatible with near-real-time deployment for closed-loop adaptive training systems.



General Conclusions

Passive BCIs for human factors assessment in operational environments

Summary and Take-home Messages

Passive BCIs are ready for the real world

The case studies demonstrate that EEG-based passive BCIs can operate outside the laboratory — in simulated and real driving, remote/telemonitoring, and real surgical settings.

EEG remains the gold standard

EEG provides millisecond-level temporal resolution and rich spectral information. Artifact removal (o-CLEAN) and channel reduction make it increasingly compatible with wearable devices.

Multimodality enhances robustness

Combining EEG, EOG, ECG/HR, EDA and even video-based signals (rPPG) provides complementary information about different facets of mental state.

From individuals to teams

The MI-based teamwork index extends passive BCI monitoring to the team level — a crucial step for complex operational environments where performance depends on cooperation.

Future Directions

- 1 Wearable & contactless integration**

Further reduction of sensor invasiveness: frontal EEG bands, rPPG from webcam, textile electrodes. Target: zero-burden monitoring systems.
- 2 Adaptive closed-loop systems**

Using passive BCI outputs to drive real-time adaptive interfaces: workload-aware automation support, drowsiness-triggered alerts, stress-adaptive task allocation.
- 3 Generalisation across domains**

Extend validated indices (MDrow, MICI) to additional high-risk domains: Air Traffic Control, military operations, industrial settings, remote healthcare.
- 4 AI-enhanced decoding**

Deep learning and transfer learning for more robust, cross-subject mental state classification without extensive individual calibration sessions.
- 5 Longitudinal & ecological studies**

Move beyond acute experiments to naturalistic, longitudinal monitoring — tracking mental state evolution over working shifts, weeks, and longer.

Thank You

Questions & Discussion

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