SOMAREALITY

WHITEPAPER

ET meets EEG

Validating Eye-Tracking–Based Biomarkers for Cognitive Load and Conscious Perception Using EEG Benchmarks

Eye Tracking meets EEG

Cognitive load and conscious perception represent two fundamental components of human cognition that underlie attention, decision-making, learning, and awareness. The ability to precisely measure and monitor these internal states has broad relevance in numerous domains, including neuroergonomics, education, human-computer interaction, and immersive technologies. Despite advances in neuroscience and behavioral research, reliably quantifying these constructs outside controlled laboratory settings remains a considerable challenge.

In this context, **SOMAREALITY** has developed two proprietary biomarkers derived from high-resolution eye-tracking data. The **Cognitive Load (CL)** biomarker leverages a combination of pupil dilation, gaze stability, and other ocular features to estimate mental workload in real-time. The **Conscious Perception Index (CPI)** quantifies the likelihood that an external event has been consciously perceived, based on gaze responses, reaction latencies, and pupillary shifts.

These biomarkers are designed to operate in real-time, offering lightweight cognitive state monitoring that can be deployed across research, education, training, and industrial applications. However, to be accepted as valid alternatives to traditional neurophysiological measures, they must show empirical convergence with established neural markers. Specifically, the CL biomarker should align with frontal theta increases and parietal alpha suppression, while the CPI biomarker should correspond with increases in fronto-parietal coherence during consciously perceived events.

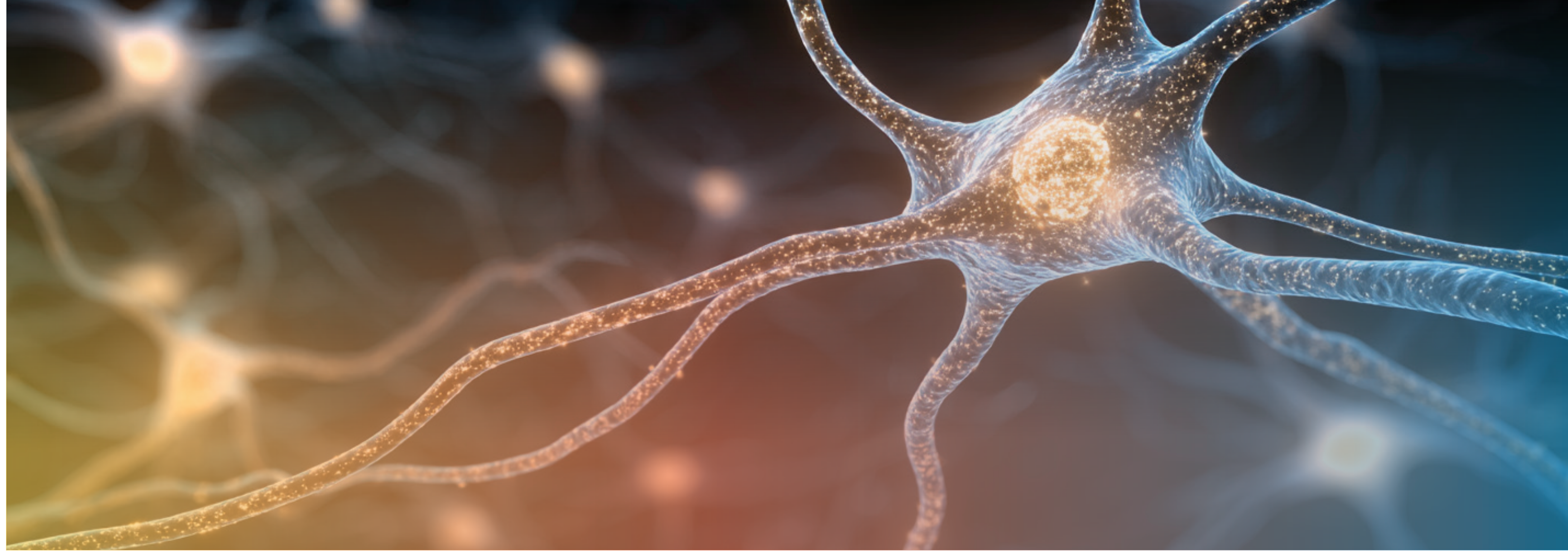
Cognitive Load and its Neural Correlates

Cognitive load (CL) refers to the demands placed on working memory and executive functions during task performance [1, 2]. As task complexity increases, so does the effort required to process, store, and manipulate relevant information. This relationship is reflected in robust neurophysiological signatures. Frontal mid-line theta oscillations (4–7 Hz), which originate primarily in the anterior cingulate cortex, have been consistently associated with increased cognitive effort, executive control, and working memory maintenance [3–5]. Simultaneously, parietal alpha activity (8–12 Hz) typically decreases with increased cognitive demand, indicating the suppression of irrelevant sensory input and heightened attentional engagement [6–8].

Conscious Perception and the Global Neuronal Work-space

Conscious perception, in contrast to subconscious processing, involves the global integration of information across distributed cortical areas. According to the Global Neuronal Workspace theory [9, 10], a stimulus becomes consciously accessible only when it is "broadcast" through recurrent interactions between frontal and parietal regions. This cortical ignition is measurable through increases in inter-regional EEG coherence or phase-locking, particularly between prefrontal and parietal sites [11, 12]. Such coherence patterns are frequently used as biomarkers of conscious access in paradigms involving visual masking, change detection, or attentional blink.

[1] J. Sweller, “Cognitive load during problem solving: Effects on learning,” Cognitive Science, vol. 12, no. 2, pp. 257–285, 1988.
[2] F. Paas, A. Renkl, and J. Sweller, “Cognitive load theory and instructional design: Recent developments,” Educational Psychologist, vol. 38, no. 1, pp. 1–4, 2003.
[3] J. F. Cavanagh and M. J. Frank, “Frontal theta as a mechanism for cognitive control,” Trends in cognitive sciences, vol. 18, no. 8, pp. 414–421, 2014.
[4] D. J. Mitchell, N. McNaughton, D. Flanagan, and I. J. Kirk, “Frontal-midline theta from the perspective of hippocampal theta,” Progress in neurobiology, vol. 86, no. 3, pp. 156–185, 2008.
[5] R. Ishii and et al., “Medial prefrontal cortex generates frontal midline theta rhythm,” Neuroreport, vol. 10, no. 4, pp. 675–679, 1999.
[6] W. Klimesch, “Eeg alpha and theta oscillations reflect cognitive and memory performance: A review and analysis,” Brain research reviews, vol. 29, no. 2-3, pp. 169–195, 1999.
[7] O. Jensen and A. Mazaheri, “Shaping functional architecture by oscillatory alpha activity: Gating by inhibition,”Frontiers in human neuroscience, vol. 4, p. 186, 2010.
[8] W. Klimesch, “Alpha-band oscillations, attention, and controlled access to stored information,”Trends in cognitive sciences, vol. 16, no. 12, pp. 606–617, 2012.
[9] S. Dehaene and J.-P. Changeux, “Experimental and theoretical approaches to conscious processing,”Neuron, vol. 70, no. 2, pp. 200–227, 2011.



Limitations of EEG and the Rise of Eye-Tracking

Although EEG provides high temporal resolution and direct access to neural dynamics, its application outside controlled laboratory environments remains constrained by its technical complexity, susceptibility to motion artifacts, and the logistical demands of setup and calibration. Moreover, while EEG offers a powerful window into neural processes, it often lacks access to the broader behavioral and contextual information that shapes and accompanies those processes. For instance, EEG alone cannot easily determine what the participant was attending to, where in the visual scene their focus was directed, or how their interaction with the environment unfolded over time. These contextual parameters are often inferred post hoc or require elaborate synchronization with external measures.

By contrast, eye-tracking offers a compelling and complementary perspective. It is noninvasive, portable, and increasingly embedded in consumer technologies such as head-mounted displays (HMDs), tablets, and smartphones. More importantly, it provides direct access to visual attention and perceptual engagement as they occur within an ecologically valid context. Knowing where a person looked, how long they fixated, when they blinked, and how their pupils responded allows for nuanced interpretations of cognitive states, often in real time and in naturalistic settings.

Pupillometry, for example, is strongly modulated by activity in the locus coeruleus noradrenergic (LC-NA) system, a central neuromodulatory hub associated with arousal, attentional control,and cognitive effort [13, 14]. Increases in pupil diameter have been consistently linked to elevated working memory demands, decision uncertainty, and mental workload [15]. Similarly, patterns of eye movements - including saccades, fixations, and blinks—have been shown to vary systematically with shifts in attentional focus and levels of cognitive engagement [16].

In the domain of conscious perception, eye-tracking reveals distinct behavioral signatures that correlate with awareness: consciously detected stimuli tend to elicit prolonged fixations, shorter reaction latencies, and enhanced pupillary dilation [17, 18]. These features not only offer indirect but sensitive markers of internal state - they also embed those markers within the visual and interactive context from which cognition arises. Thus, while EEG excels in capturing rapid neural responses, eye-tracking uniquely situates those responses within the perceptual and task-relevant landscape in which they occur.

[10] G. A. Mashour, P. Roelfsema, J.-P. Changeux, and S. Dehaene, “Conscious processing and the global neuronal workspace hypothesis,” Neuron, vol. 105, no. 5, pp. 776–798, 2020.
[11] C. Sergent and S. Dehaene, “Is consciousness a gradual phenomenon? evidence for an allor-none bifurcation during the attentional blink,” Psychological science, vol. 15, pp. 720–728, 2004.
[12] R. Gaillard and et al., “Converging intracranial markers of conscious access,” PLoS biology, vol. 7, no. 3, e61, 2009.
[13] G. Aston-Jones and J. D. Cohen, “An integrative theory of locus coeruleus-norepinephrine function: Adaptive gain and optimal performance,” Annual review of neuroscience, vol. 28, 2005.
[14] P. R. Murphy and et al., “Pupil diameter covaries with bold activity in human locus coeruleus,”Human brain mapping, vol. 35, no. 8, pp. 4140–4154, 2014.
[15] N. Unsworth and M. K. Robison, “Pupillary correlates of lapses of sustained attention,”Cognitive, Affective, & Behavioral Neuroscience, vol. 16, no. 4, pp. 601–615, 2016.
[16] K. Holmqvist and et al., Eye Tracking: A comprehensive guide to methods and measures. Oxford University Press, 2011.
[17] C. M. Privitera and et al., “Pupil dilation during recognition memory,” Psychophysiology, vol. 47, no. 3, pp. 451–455, 2010.
[18] S. M. Wierda and et al., “Pupil dilation deconvolution reveals the dynamics of attention at high temporal resolution,” PNAS, vol. 109, no. 22, pp. 8456–8460, 2012.

From EEG ...

Strengths of EEG

+ **Direct Neural Measurement**
  Captures electrical activity from the brain, providing direct insights into cognitive processes.

+ **High Temporal Resolution**
  Excellent for tracking rapid cognitive changes (millisecond precision).

+ **Cognitive State Detection**
  Effective for identifying mental workload, fatigue, and emotional states

+ **Portable Options**
  Modern wireless EEG systems allow for mobile applications.

Weaknesses of EEG

- **Lack of Contextualization**
  Brain activity alone is often not sufficient to create additional value, but requires additional context.

- **Signal Noise**
  Susceptible to artifacts from muscle movements and environmental interference.

- **Setup Complexity**
  Requires proper electrode placement and gel application.

- **Participant Discomfort**
  Can be uncomfortable during prolonged use.

- **Poor Spatial Resolution**
  Difficulty in precisely localizing brain activity.

- **Limited Ecological Validity**
  Requires controlled environments.

... to Eye Tracking

Strengths of Eye Tracking

+ **Combines insights into Cognitive Activities with Visual Context**
  In contrast to EEG, Eye Tracking allows not only insights that there is cognitive activity, but also the context where the interaction is directed at.

+ **Natural Behavior Measurement**
  Captures gaze patterns without interfering with tasks.

+ **High Spatial Resolution**
  Precise tracking of where attention is directed.

+ **Ecological Validity**
  Works well in real-world environments.

+ **Non-Intrusive**
  Minimal setup required; participants often forget they're being tracked.

+ **Easy Integration**
  Works well with other technologies (e.g., VR, mobile devices).

Weaknesses of Eye Tracking

- **Environmental Constraints**
  Affected by lighting conditions and obstructions.

- **Indirect Measurement**
  Cannot measure brain activity or cognitive states

Hardware

The Bittium NeurOne Tesla is a professional-grade electroencephalography (EEG) system designed for high-precision neuroscience research and clinical applications. This advanced EEG solution combines state-of-the-art hardware with sophisticated software capabilities to provide researchers with a comprehensive tool for brain activity measurement and analysis.

EEG

Recording Devices

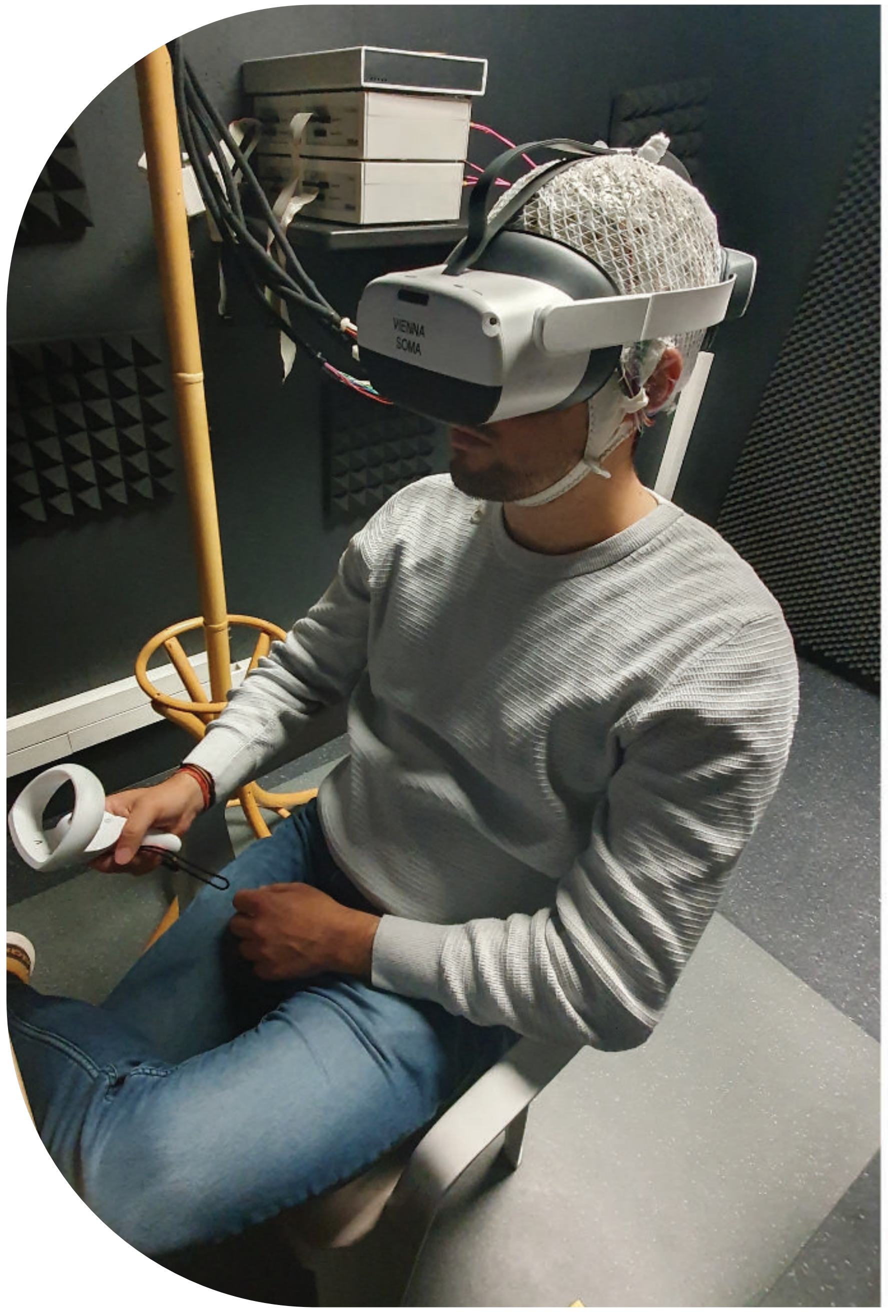
- Bittium NeurOne Tesla EEG System with 2 amplifiers:
  - 64 passive electrodes (10-20 system)
  - Sampling rate: 1 kHz
- PC for the NeurOne EEG recording software and casting the VR screen (two monitors necessary

Technical Specifications

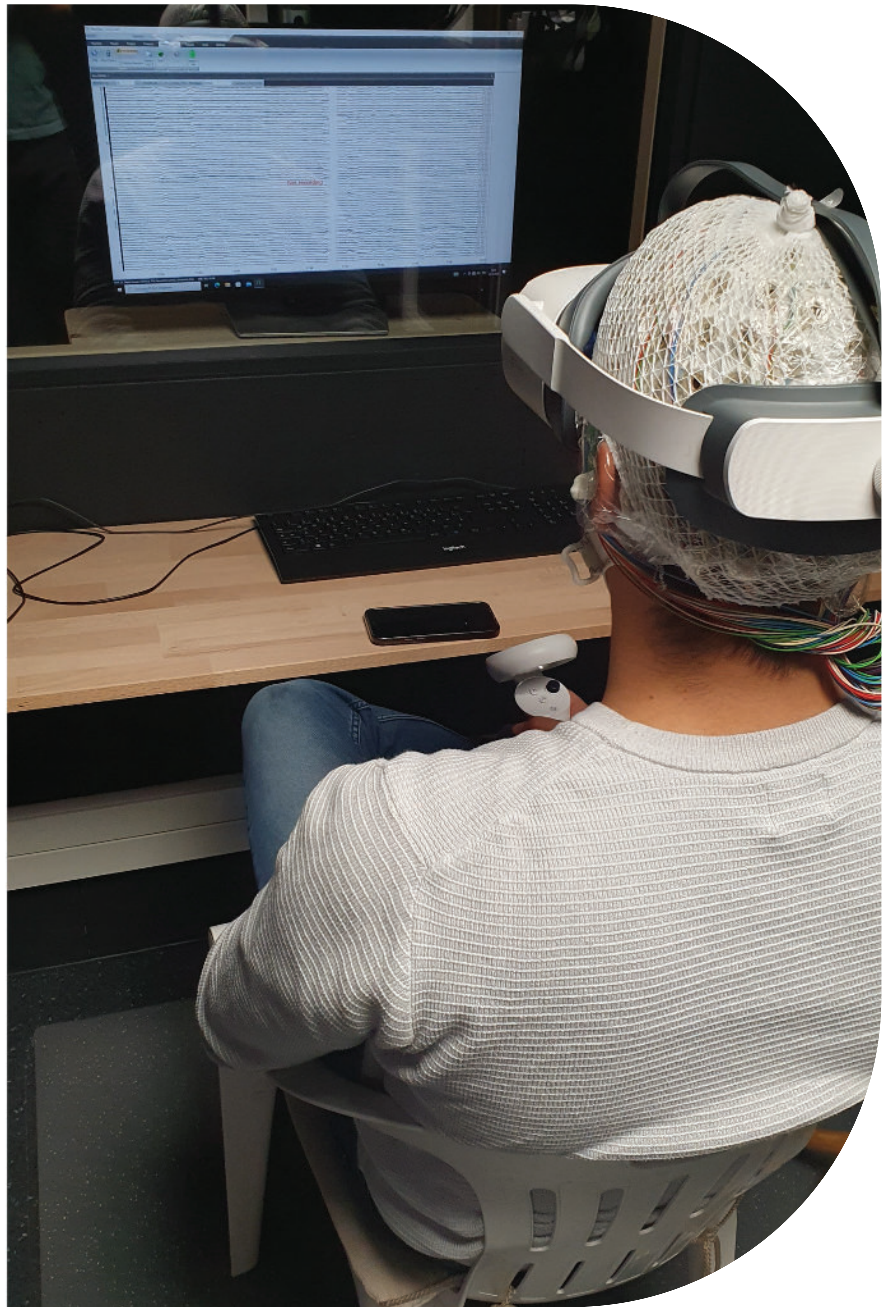
- 64-channel configuration
- Sampling Rate: Up to 5000 Hz per channel
- Resolution: 24-bit ADC with 0.029 μV LSB
- Input Range: ±25 mV (software-selectable)
- Input Impedance: >100 MΩ
- CMRR: >120 dB at 50/60 Hz
- Noise Level: <0.5 μVpp (0.1-100 Hz bandwidth)

Recorded Signals

- 64-channel EEG data in BrainVision format:
  - Text header file (.vhdr)
  - Test marker file (.vmrk)
  - Binary data file (.eeg)



The PICO Neo 3 Pro Eye is an advanced standalone virtual reality (VR) headset with integrated eye-tracking technology, designed for professional applications in research, training, and enterprise environments. Building upon PICO's VR platform, the Neo 3 Pro Eye combines high-resolution displays with precise eye-tracking capabilities to enable sophisticated gaze-based interactions and cognitive research applications.



Integrated Eye Tracker

Recording Devices

- Pico Neo 3 Pro Eye (stand-alone HMD)
  - Frame rate: 72 fps
  - Tobii Ocumen (research license) for advanced eye-tracking metrics

Technical Specifications

- Accuracy: <0.5° visual angle (typical)
- Precision: <0.1° RMS
- Latency: <10ms (from gaze detection to data output)
- Tracking Range: ±20° horizontal, ±15° vertical
- Calibration: 9-point calibration procedure with automatic validation
- Gaze Data Output: Binocular gaze points, pupil diameter, eye openness

Recorded Signals

- Eye tracking data:
  - Aware diagnostics files (.awr)
  - CL files (.awr and .csv)
- Event marker files (.csv)
- Change detection markers (.csv)
- Screen recordings (.mp4)

Experiment Design

This study aims to evaluate the degree to which SOMAREALITY's eye-tracking–based biomarkers replicate well-established EEG markers of cognitive load and conscious perception. We present a novel dual-task paradigm conducted in virtual reality (VR), wherein participants engage in a cognitively demanding task (counting vehicles based on number sequences) while observing a dynamic virtual environment in which background elements change. This design is intended to elicit both high and low states of cognitive load, as well as variation in conscious perception depending on task instructions and participant awareness.

EEG and eye-tracking data are recorded simultaneously, allowing for direct comparisons across modalities. If strong correlations are observed between the CL and CPI biomarkers and their respective EEG counterparts - frontal theta, parietal alpha, and fronto-parietal coherence - this would provide compelling evidence for the scientific validity of these non-invasive, scalable measures. More broadly, such results would demonstrate the feasibility of deploying ye-tracking as a tool for cognitive state monitoring in applied research, education, training, and other high-impact domains.

The experimental environment was realized through a custom-built virtual reality (VR) scenario. Participants were seated in a virtual room, positioned to face an open window overlooking a street scene, viewing numbered vehicles passing by. Behind the street, a detailed urban environment was rendered, featuring a building facade and sidewalk populated with various interactive elements such as post boxes, air conditioning systems, windows, or staircases. These background elements were programmed to undergo subtle, randomized changes, including alterations in color, disappearance, or reappearance, serving as stimuli for the conscious perception task.

The conducted EEG/eye tracking study involved a total of 20 healthy adult participants with normal or corrected-to-normal vision. Participation was voluntary, and all individuals provided informed consent following institutional ethical guidelines. The sample was balanced in terms of age and gender to ensure generalizability of the results, although no formal stratification was employed.

Experiment Parameters

Primary Task: Modulating Cognitive Load (CL)

To manipulate cognitive load in a controlled manner, participants completed a sequence of five tasks involving the monitoring and counting of passing vehicles, each labeled with a digit from 0 to 9. Each task introduced a specific set of rules which vehicles should be counted and how the mental counter should be adjusted. Target stimuli appeared less frequently than non-target stimuli to increase difficulty and evoke event-related potentials such as the P300, known to reflect decision-making and categorization processes.

Task complexity increased with each subsequent task, based on the following counting rules:

1. Task 1: Count vehicles labeled with the number "5"; increment the counter by one for each occurrence.
2. Task 2: Count vehicles labeled "1" or "3"; increment the counter by one.
3. Task 3: Count vehicles labeled "2", "4", or "6"; increment the counter by two.
4. Task 4: Count all even-numbered vehicles; increment by two for each. Subtract one when a vehicle labeled "0" appears.
5. Task 5: Count all odd-numbered vehicles; increment by three for each. Subtract two for every "0".

Each trial lasted 90 seconds. As the complexity of the counting rules and arithmetic operations increased across tasks, so did the cognitive demands placed on working memory, executive function, and sustained attention.

Secondary Task: Assessing Conscious Perception (CPI)

Simultaneously, participants were exposed to a series of subtle changes in the background environment designed to probe their conscious perception. This secondary task unfolded in two distinct phases to assess both implicit and explicit perceptual awareness:

1. Phase 1 (Uninformed): Participants were not informed that visual elements in the background would change. After completing all five primary tasks, they were asked retrospectively whether they had noticed any such changes and, if so, to specify during which tasks.
2. Phase 2 (Informed): Participants were explicitly instructed to monitor the environment for changes and to report them by pressing a button as soon as they were detected.

This two-phase structure enabled the differentiation between implicit and explicit detection of environmental changes, thus supporting a graded measure of conscious perception.

Experimental Procedure

The experimental session spanned approximately 30 minutes and followed a consistent structure to ensure comparability across participants:

1. Test Run (5 minutes): Participants were introduced to the VR environment and practiced the primary counting task.
2. Run 1 (10 minutes): Execution of all five CL tasks under the uninformed condition for CPI (Phase 1).
3. Retrospective Questionnaire (2 minutes): Participants reported whether they noticed any environmental background changes.
4. Break (3 minutes): A brief pause to minimize fatigue effects and cognitive overload.
5. Run 2 (10 minutes): Repetition of all five CL tasks, this time under the informed condition for CPI (Phase 2).

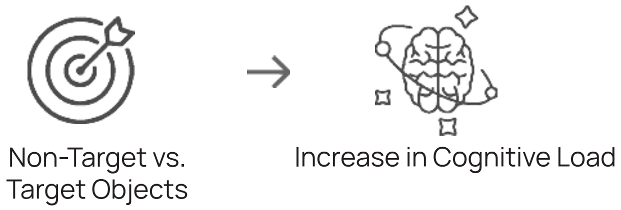
Hypotheses and Analytics Approach

Experiment Hypothesis

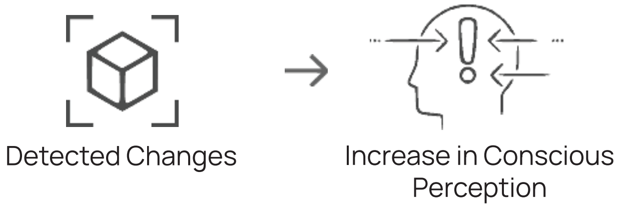
The experimental paradigm was structured around five hypotheses, each targeting a specific neurocognitive dimension:

- **Hypothesis 1 (H1):** The car-counting task will induce measurable increases in cognitive load, with more complex tasks and dual-task conditions (Phase 2) leading to higher CL.

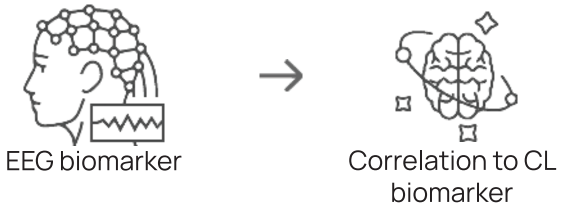
- **Hypothesis 2 (H2):** CL will be significantly elevated during the viewing of target vehicles, reflecting task engagement and decision-making demands.



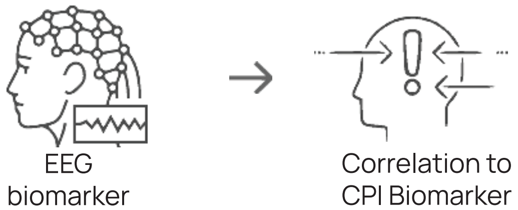
- **Hypothesis 3 (H3):** Background changes that are consciously detected will correspond with higher CPI scores than undetected changes.



- **Hypothesis 4 (H4):** The eye-tracking-based CL biomarker will show a positive correlation with frontal theta power and a negative correlation with parietal alpha power, and will replicate behavioral differences noted in H2.



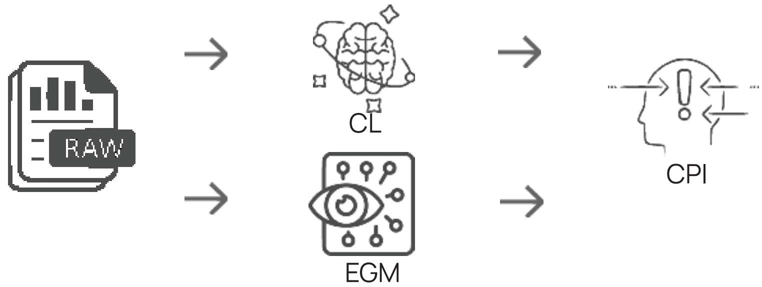
- **Hypothesis 5 (H5):** The EEG-based conscious perception marker will correlate significantly with the CPI biomarker derived from eye-tracking data and will replicate detection-related effects predicted in H3.



Eye-Tracking Analysis

Eye-tracking data were split into three main categories of metrics:

- **Real-time CL Metrics:** Extracted using the Tobii Ocumen SDK during online data acquisition, these metrics captured dynamic fluctuations in workload-related gaze behavior.
- **Extended Gaze Metrics (EGM):** The comprehensive analytics framework by SOMAREALITY allows gaze behavior and pupillometric data, resulting in statistical features on fixations, saccades, gaze distributions, etc.
- **Conscious Perception Index (CPI):** Derived from the EGM framework and built with proprietary algorithms to quantify the degree of conscious awareness of the participant while performing the primary and secondary tasks.



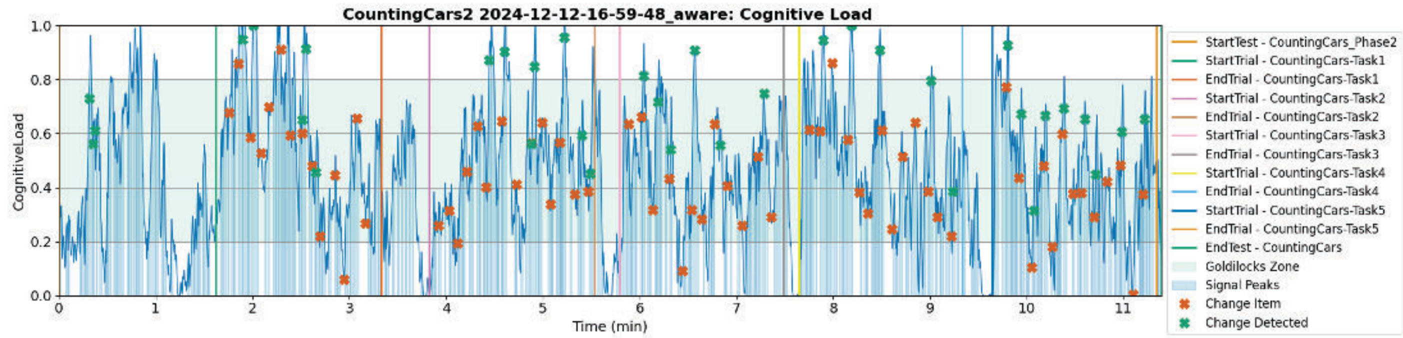
EEG Analysis

EEG preprocessing was performed using the MNE-Python toolbox. This included bandpass filtering, artifact rejection via ICA, and segmentation into task-aligned epochs. Spectral analysis focused on power spectral density (PSD) within two key frequency bands:

- **Theta (4–7 Hz):** Associated with working memory, cognitive control, and increased mental workload.
- **Alpha (8–13 Hz):** Inversely related to mental effort and sensory attention, particularly in posterior regions.

Increasing cognitive demand elicits increased theta power over frontal and central electrodes, alongside a simultaneous suppression of alpha power in parietal and occipital regions. Conscious perception was assessed through functional connectivity, measured as coherence between prefrontal and parietal regions - an established signature of integrative neural processing underlying awareness.

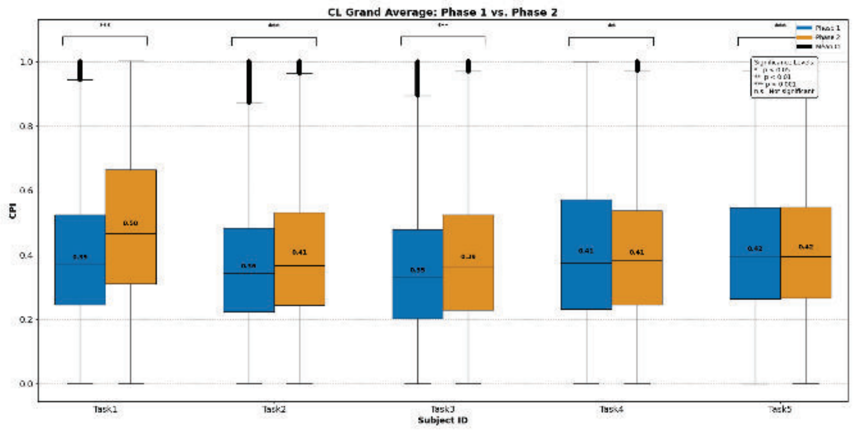
Results



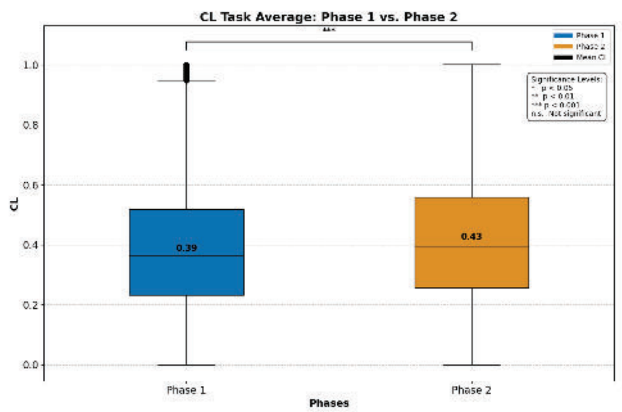
This plot shows an example of a raw CL signal of a phase 2 trial: Event markers show the start and the end of individual tasks. Background changes are highlighted with a red cross, and detected changes with a green cross.

Hypothesis 1 - Increasing Cognitive Load with Increasing Task and Phase Difficulty

One of the aspects this study explored is the dependency between task complexity and required cognitive load. This hypothesis posited that CL will be significantly higher during more complex tasks, reflecting greater amounts of cognitive resources being required for the processing.



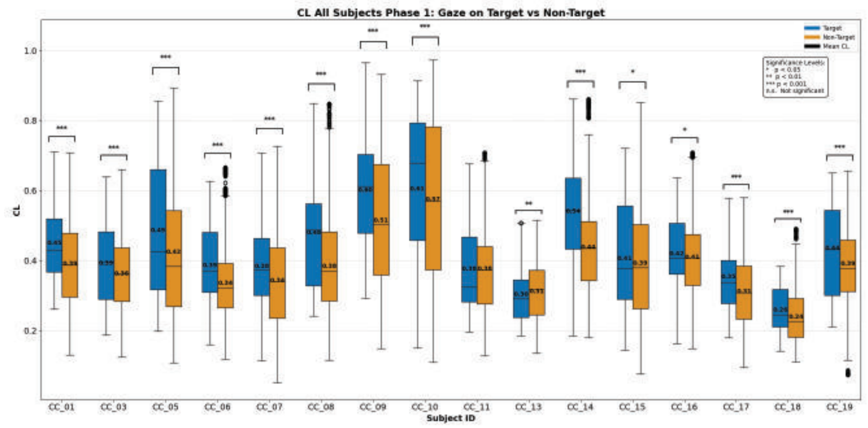
Analyzing average CL per task and comparing phase 1 and phase 2, we can observe a drop in CL, likely due to a learning effect and environmental adaptation. At Tasks 4 and 5, CL increases again, supporting our hypothesis that cognitive load increases with task difficulty.



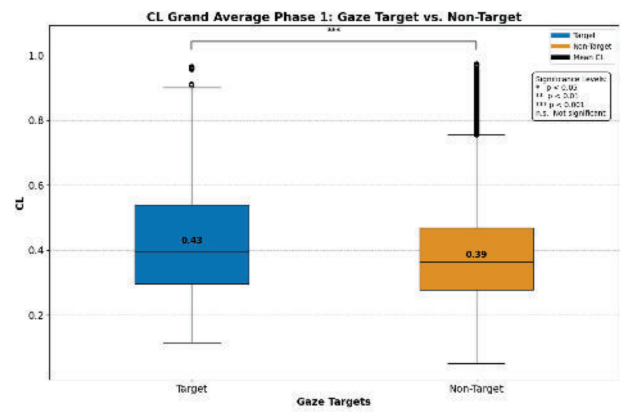
In a global comparison of the Tasks between Phase 1 and Phase 2, **a statistically significant increase in CL** ($p < 0.001$) is observed for individual tasks and overall averages, **thus confirming hypothesis 1**. Although a greater difference between tasks was expected, participant feedback suggested that the task difficulty was not sufficiently high.

Hypothesis 2 - CL is higher when looking at Target Cars than Non-Target Cars

For the second research question, the study explored is the dependency between target and non-target processing and associated cognitive load. This hypothesis posited that CL will be significantly higher during processing of target objects since this requires the execution of additional mental tasks.

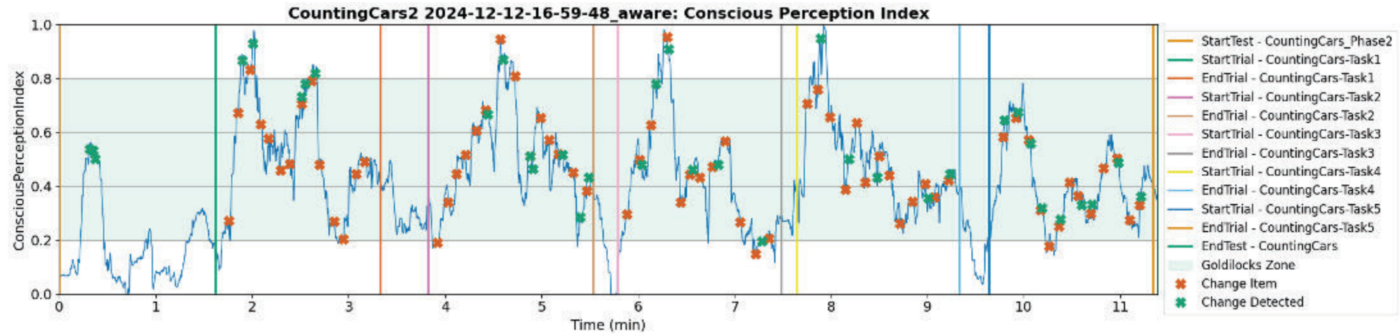


In this figure, it can be observed how in nearly all cases, individual participant CL levels were higher when viewing target in contrast to non-target cars. This reflects the increased cognitive demand of counting, memorizing, and updating target cars.



The aggregated comparison of Cognitive Load comparing the processing of target vs. non-target cars reveals a **statistically significant increase in CL ($p < 0.001$) when looking at target cars, thus confirming hypothesis 2.**

Results

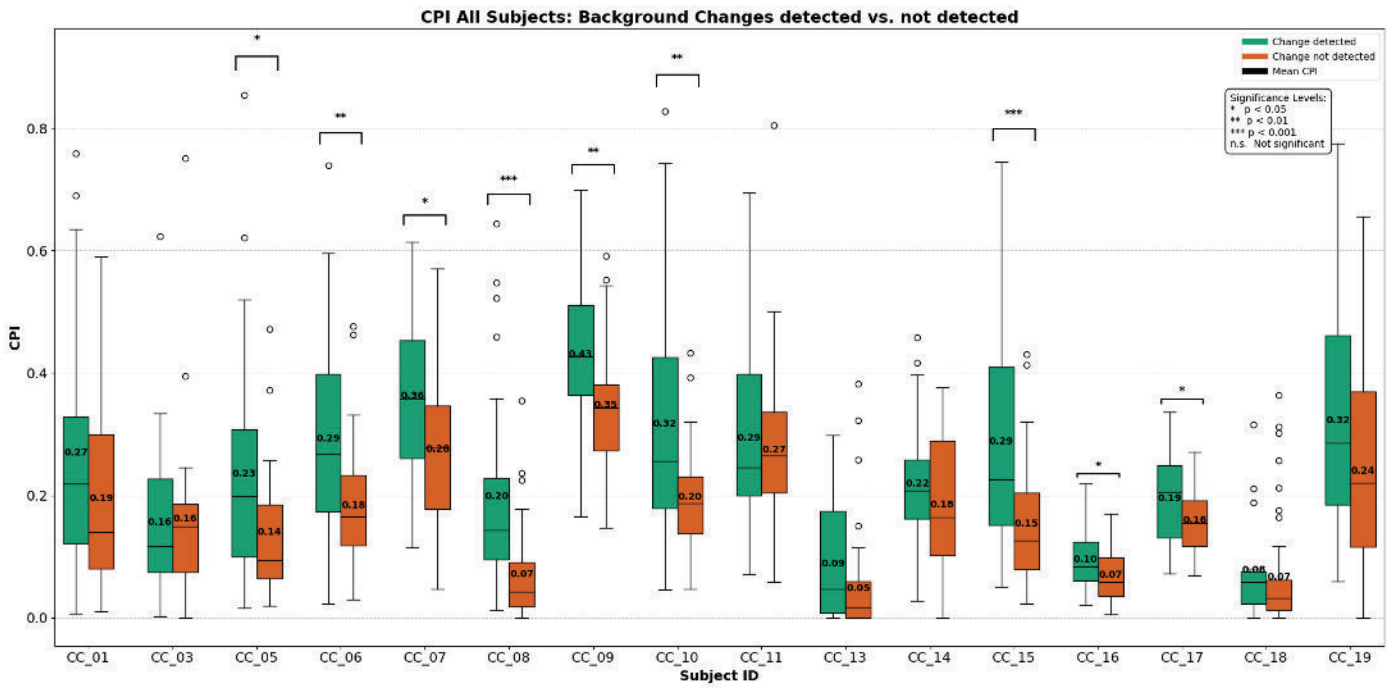


This plot shows an example of a CPI signal of a phase 2 trial smoothened with a moving average filter: Event markers show the start and the end of individual tasks. Background changes are highlighted with a red cross, and detected changes with a green cross.

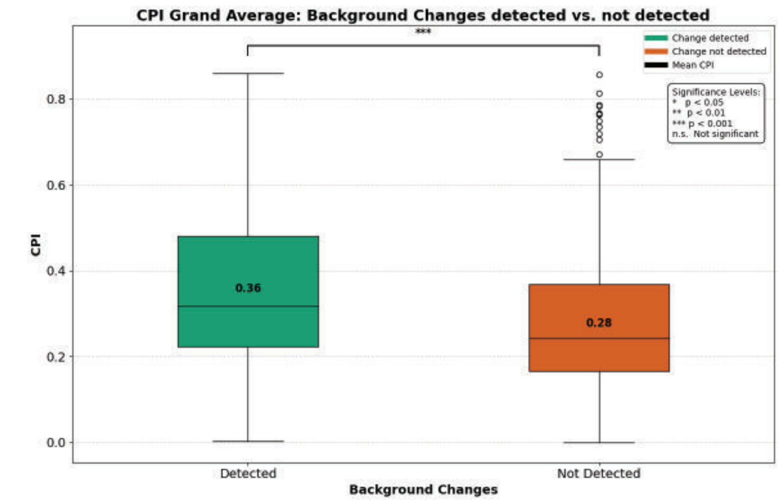
Hypothesis 3 - Detected Background Changes elicit higher CPI than Undetected Changes

This study examined the relationship between conscious perception and background change detection in a dual-task paradigm. This hypothesis posited that detected background changes would elicit significantly higher Conscious Perception Index (CPI) scores compared to undetected changes, reflecting greater cognitive processing and awareness of visual modifications.

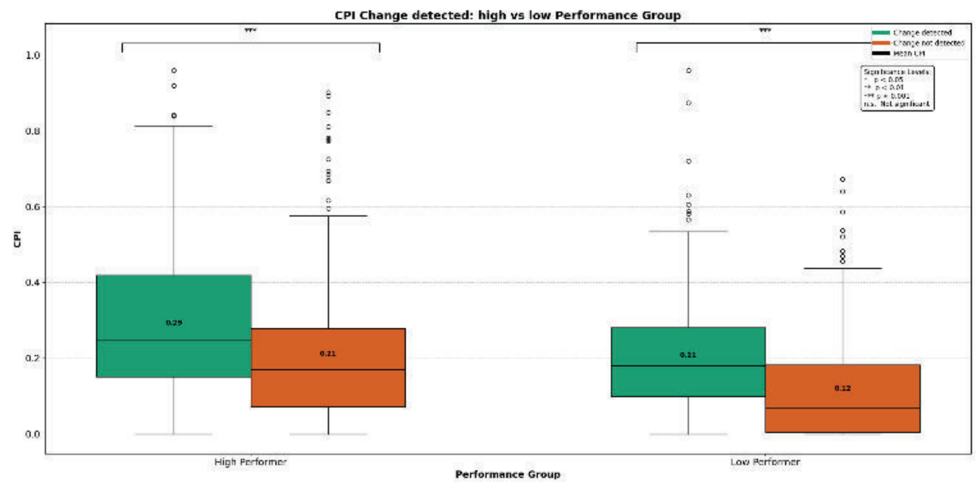
In the following plots, we present our findings regarding the differential CPI scores associated with detected versus undetected background changes. These results provide empirical evidence regarding the relationship between conscious perception and cognitive processing intensity during visual change detection tasks.



The comparison of the CPI in cases where participants detected background changes with those where they did not, shows across all participants, that the conscious detection coincided with higher CPI levels. This suggests that conscious perception of changes during tasks adds to cognitive processing.



The grand average comparison shows a **statistically significant increase in CPI (p < 0.001) when background changes were detected**, thus **confirming hypothesis 3**.

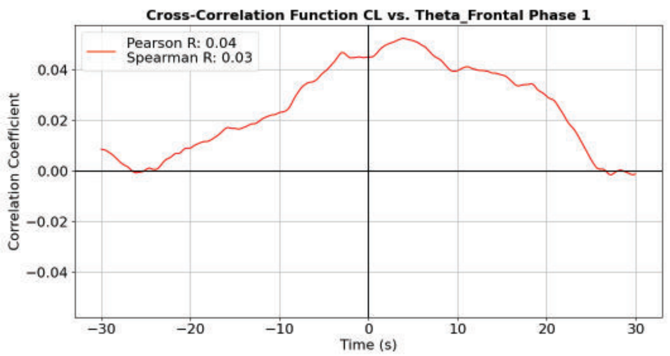


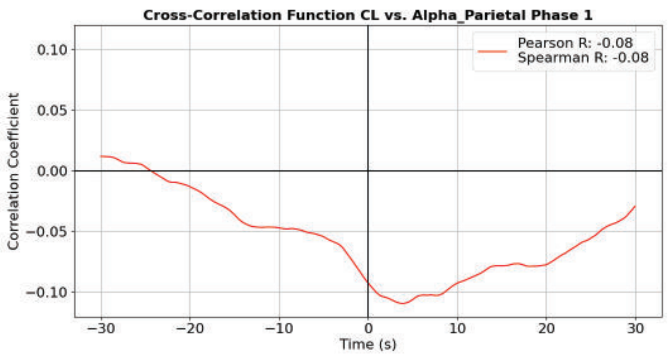
Additionally, further analysis shows performance levels based on detection rates. Participants were split into high and low performers using a median split. The results suggest that **higher CPI is associated with better detection performance**.

Results

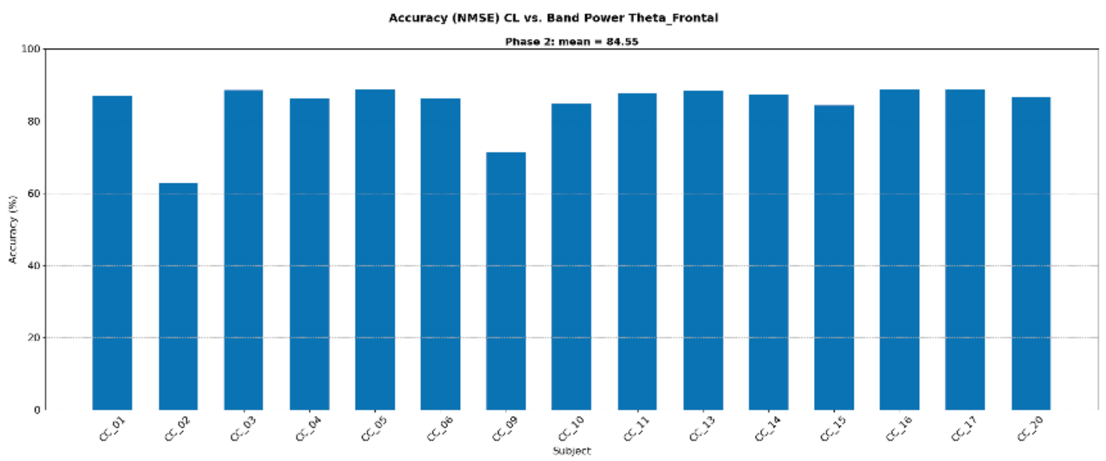
Hypothesis 4 - EEG features of Cognitive Load correlate with our CL Biomarker

In the following, we present the findings from our comprehensive study comparing EEG features and eye-tracking-based analytics as measures of cognitive load. Our investigation aimed to elucidate the distinct and overlapping insights provided by these two methodologies in assessing cognitive states. Analyzing EEG data, we used specific neural correlates indicative of varying cognitive load levels, while eye-tracking metrics offered a complementary perspective through the SOMAREALITY cognitive load biomarker. This comparative analysis underscores the expressiveness and reliability of the eye-tracking based approach in comparison to EEG as a gold standard, and paves the way for integrating these methods to achieve a more holistic evaluation of cognitive processes.

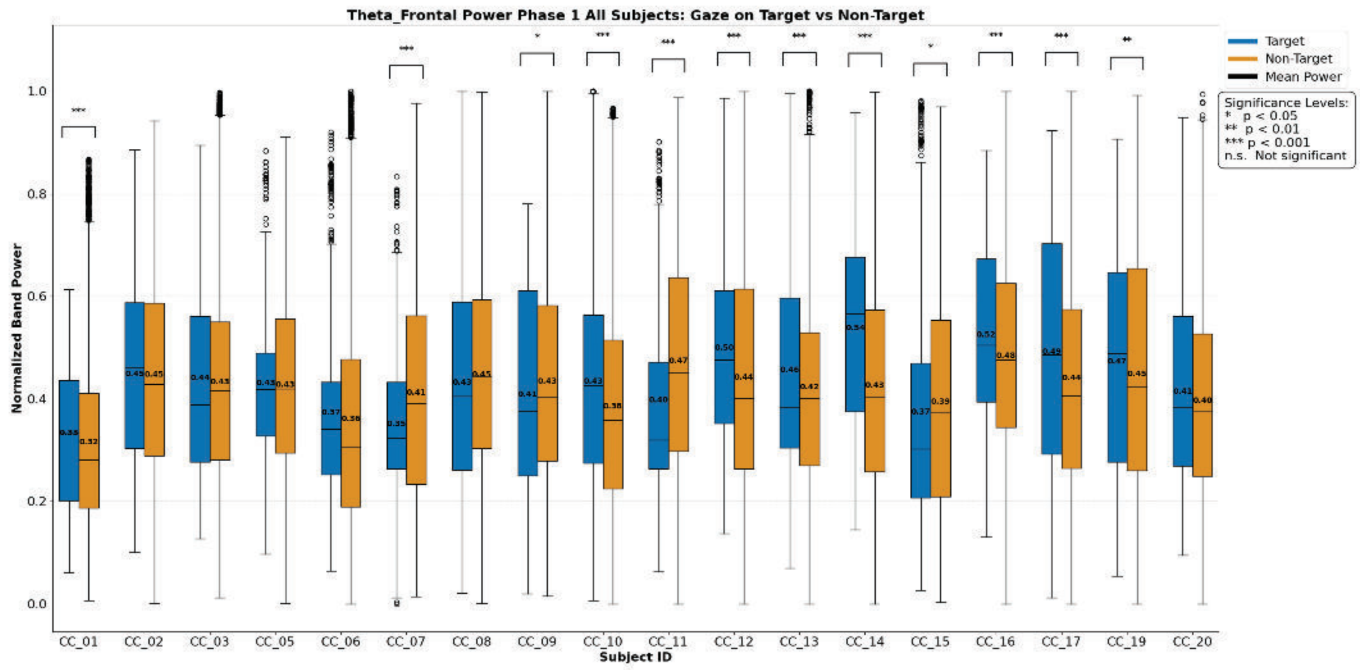




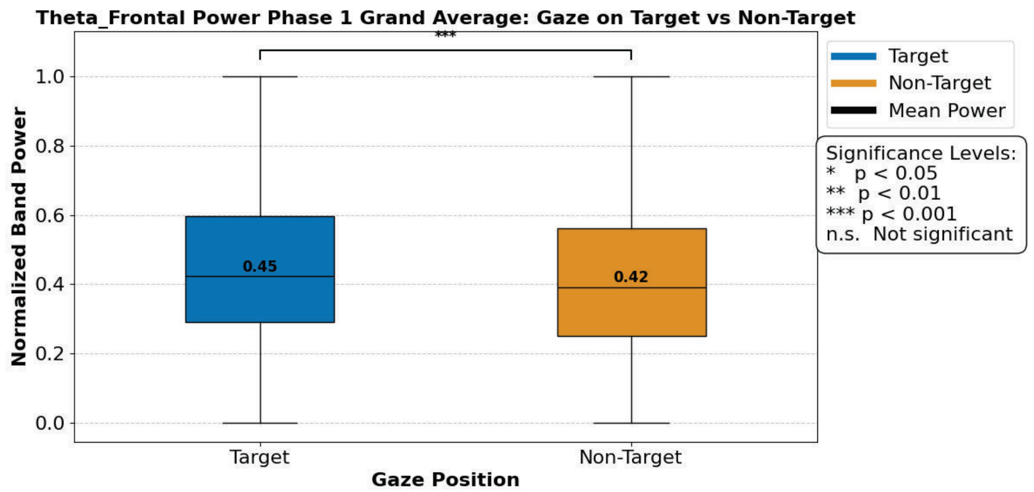
Analyzing the correlation between CL and EEG features, the plots above display the grand average cross-correlation (average over all participants) between our CL biomarker and EEG features. While the first figure shows a positive correlation between frontal theta power and CL, the second figure shows a negative correlation between parietal alpha power and CL, supporting our hypothesis.



The accuracy shows the level of similarity between the frontal theta band power signal and our CL biomarker signal. This metric was calculated with the normalized mean squared error (NMSE) between the two signals. A mean accuracy of 84.55% was achieved across participants.



Analyzing frontal theta band power of individual participants, looking at target cars elicits a consistently higher power than looking at non-target cars.

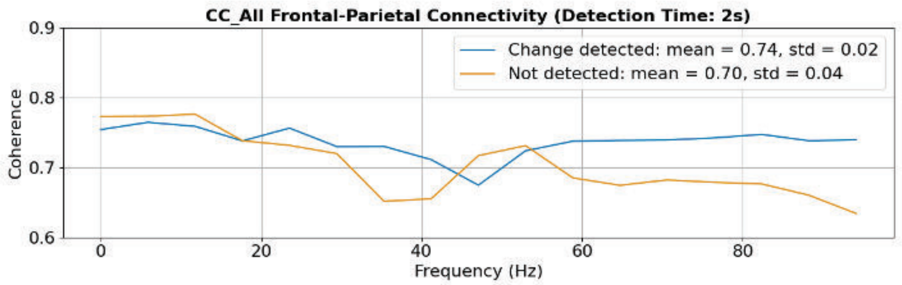


The Grand Average analysis of Frontal Theta Power shows a **highly statistically significant increase ($p < 0.001$)** when looking at target cars vs. looking at non-target cars **which correlates with our CL biomarker results and confirms our hypothesis.**

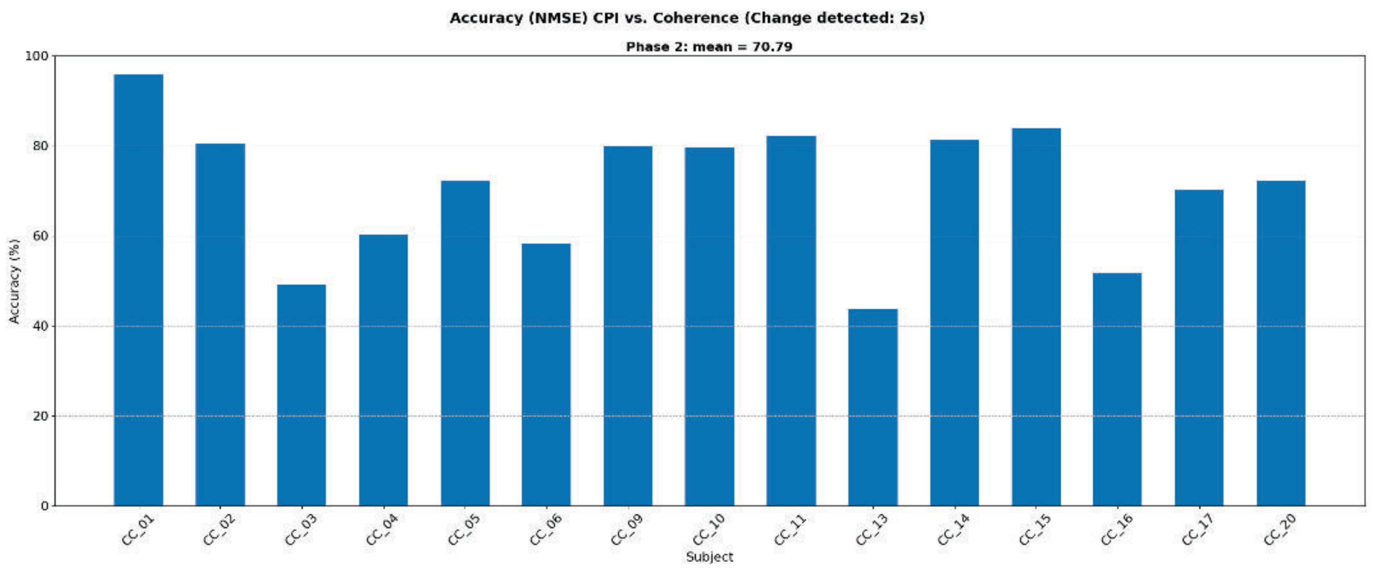
Results

Hypothesis 5 - EEG Features of Conscious Perception correlate with our CPI Biomarker

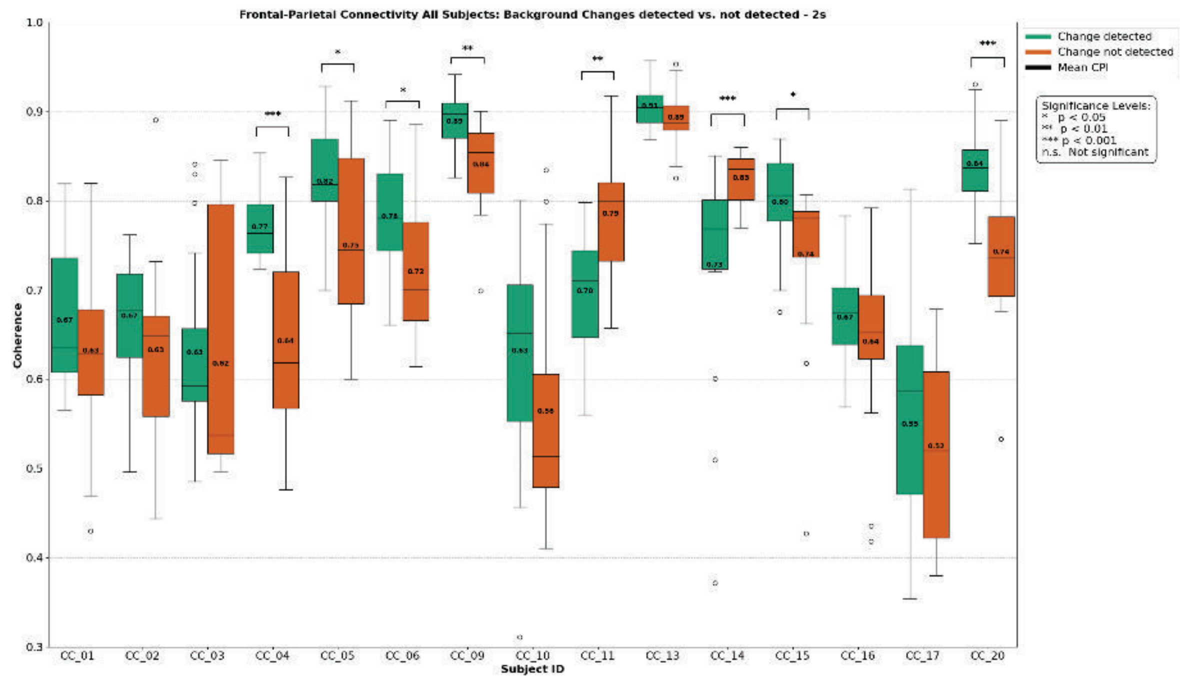
The correlation between these two sets of biomarkers holds significant promise for unraveling the neural mechanisms underlying conscious perception. By examining how specific EEG patterns align with eye tracking metrics, researchers aim to identify robust biomarkers that can objectively measure and predict levels of conscious awareness. This interdisciplinary approach not only enhances our understanding of the neural correlates of consciousness but also paves the way for developing innovative diagnostic and therapeutic tools for conditions affecting cognitive and perceptual functions. In EEG analysis, conscious perception is indicated by increased coherence between prefrontal and parietal regions, meaning, higher coherence reflects stronger connectivity and, thus, greater conscious awareness.



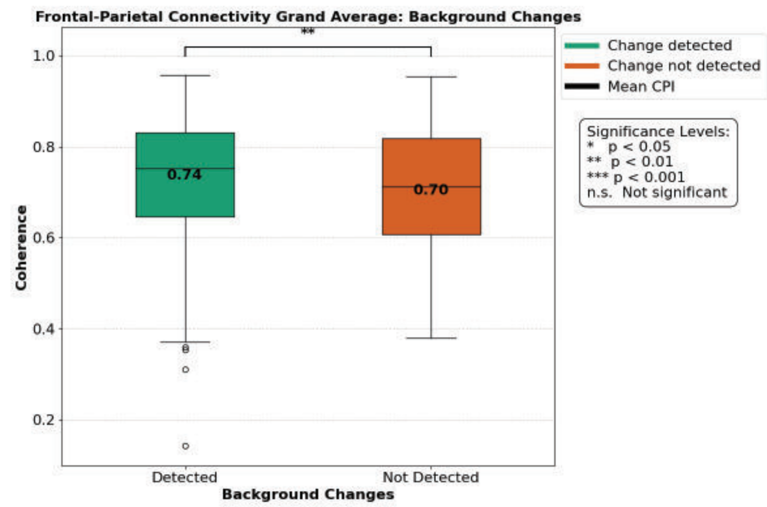
When looking at the average coherence over participants across different frequencies, significant differences between detected and undetected background changes can be found in the gamma frequency band (> 30 Hz), which is associated with task-specific neuronal synchronization.



he Accuracy shows the level of similarity between the coherence (fronto-parietal connectivity) and our CPI biomarker signal, combining detected and undetected background changes. The accuracy was calculated with the normalized mean squared error (NMSE) between the two signals. A **mean accuracy of 70.79% was achieved across participants.**



Coherence of individual participants when comparing detected and undetected background Changes: Detection is associated with statistically significantly higher coherence across all participants.

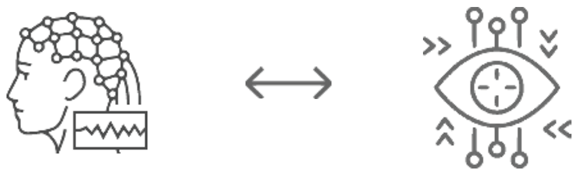


The Grand Average comparison of detected and undetected background changes shows a highly statistically significant ($p < 0.01$) increase in coherence during background change detections, **which correlates with our CPI biomarker results and confirms our hypothesis.**

Discussion & Conclusions

Discussion

This study advances the field of applied cognitive neuroscience by demonstrating the feasibility of validating gaze-based biomarkers against established EEG correlates. The observed alignment between ocular metrics and neural signatures not only strengthens the theoretical grounding of SOMAREALITY's proprietary Cognitive Load (CL) and Conscious Perception Index (CPI) algorithms but also underscores the broader potential of eye-tracking for scalable cognitive monitoring.



Importantly, eye-tracking offers contextual richness that EEG alone cannot provide. While EEG captures neural dynamics with high temporal precision, it lacks direct information about visual attention targets, environmental interactions, or scene-based context. In contrast, gaze data can reveal precisely where and when attention is directed - whether toward a changing object, a relevant stimulus, or a distractor - thus anchoring internal states within concrete perceptual events. This added dimension is particularly advantageous in naturalistic settings such as driving, learning, or VR-based simulations, where behavioral context plays a critical role in cognitive interpretation.

Nonetheless, the deployment of gaze-based biomarkers in real-world environments requires careful calibration. Ocular metrics can be influenced by lighting conditions, device ergonomics, and inter-individual variability. Future research could incorporate cross-context validation studies and explore multi-modal sensor fusion - combining eye-tracking with physiological signals such as electrodermal activity (EDA) or heart rate variability (HRV) - to enhance robustness and reliability.

Conclusion

By systematically validating SOMAREALITY's eye-based biomarkers - Cognitive Load (CL) and Conscious Perception Index (CPI) - against neural markers such as frontal theta power, parietal alpha suppression, and fronto-parietal coherence, this study offers empirical support for the use of eye-tracking as a credible proxy for internal cognitive states. The findings bridge a critical gap between laboratory-grade neuroscience and scalable, real-world applications. As a result, they lay the foundation for future adaptive technologies that are both neuro-informed and human-centered, capable of dynamically responding to user cognition in real time.

What you need...

Eye Tracker

Provides pupil dilation levels in real-time with no restrictions to movement and minimal intrusiveness.

AR/VR Headsets with integrated Eye Tracking

Wearable Eye Tracker

Remote Eye Tracker

Requirements towards Eye Tracker and API

open access to relevant data streams

- pupil dilation
- pupil dilation confidence
- world camera image (or screen image capture)

Wired or wireless connection (WIFI) for live data streaming

Soma Aware SDK for Data Processing & Analytics

Enables the analysis of raw eye tracking data and provides insights on Cognitive Load levels in real-time and via extensive offline reports

Soma Aware SDK provides

Free Hardware Choice
Compatibility with most available Eye Trackers

Brightness Compensation
From the lab into real-world applications via compensation of environmental brightness

Real-time Insights
Obtaining expressive, continuous Cognitive Load measures in real-time

In-Task Analytics
Integration in processing and analytics processes

Green Field Capability
Complete freedom of motion for your Cognitive Load Studies

Contextualization
Combination with further SOMA biomarkers (Visual Attention, Perception, Consciousness)

Team

At SOMAREALITY, we believe in a world where everyone can unlock their full cognitive potential. Therefore, we develop scientifically validated digital biomarkers to enable technologies in industry, health care, society and beyond.

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