SOMAREALITY

WHITEPAPER

Attention Types

Analyze and interpret attentional gaze behavior to better understand user interaction

Understanding Attention...

Analysis of attentional behavior via Attention Type Classification (ATC)

In an era marked by constant information influx and increasing cognitive demands, understanding the mechanisms of attention has become more important than ever. Attention is a fundamental cognitive process that enables individuals to navigate complex environments, prioritize stimuli, and execute tasks effectively. From neuroscience to behavioral psychology, the study of attention spans numerous disciplines, each contributing unique insights into its nature, types, and practical applications.

This whitepaper explores the multifaceted concept of attention, with a focus on its different types and their implications for human behavior and technology. Attention is not a monolithic phenomenon but a dynamic interplay of various subtypes, each serving distinct functions. Broadly, these types can be categorized into **Sustained Attention, Selective attention, and Switched / Divided Attention**, among others. Each type plays an important role in our daily lives, from maintaining focus during a meeting to multitasking in fast-paced environments.

In our implementation of attention type classification, we limit the model to two categories: Focused Attention - which combines Sustained and Selective Attention - and Switched Attention. This choice is motivated by the fact that reliably distinguishing between selective and sustained attention would require privacy-sensitive analysis of users' environmental context, which we intentionally avoid.

The significance of understanding attention extends beyond theoretical frameworks. In the modern age, industries such as education, healthcare, marketing, and technology have harnessed insights from attention research to optimize outcomes. For instance, educators design curricula that cater to attention spans, marketers craft campaigns that capture consumer interest, and developers create interfaces that align with cognitive load principles.

In this white paper, we aim to provide a comprehensive (i) overview of the types of attention and their underlying mechanisms, (ii) how they can be measured and modeled, (iii) presentation of validation studies, and (iv) their real-world applications. By bridging scientific theory with practical insights, we hope to illuminate how attention shapes human experience and how an improved understanding of this phenomenon can drive innovation across domains.

Attention Type Descriptions

Focused Attention

Sustained Attention

Sustained Attention is the capacity to maintain focus over longer periods of time, i.e., for tasks that require prolonged concentration, such as monitoring or attending long meetings.

Selective Attention

Selective Attention enables prioritization of important information by focusing on a specific stimulus while ignoring irrelevant ones, such as recognizing a voice in a noisy room.

Switched Attention

Divided Attention

Switched attention allows for efficient transitions between tasks or stimuli. It supports multitasking, like managing emails while on a conference call.

01 Our Vision

We are convinced that eye tracking and the features it provides, represents the key to unobtrusive, accurate and efficient cognitive assessments. We expect innovative and superior technologies such as eye tracking to improve and replace established pen and paper methodologies in the near future.

02 Our Mission

For this purpose, we explore and build eye tracking-based technologies to analyze, interpret and evaluate cognitive functions for various applications in industry, health care and society, such as, diagnostics, optimization of performance, training and education, as well as safety systems.

Key Benefits with Eye Tracking-based Cognitive Insights

Direct Measurement

With eye gaze being a substantial representative of perception and cognition, eye tracking-based systems open the door for new levels of cognitive insights.

Overcoming limitations of traditional tests

Traditional cognitive assessments (often pen & paper) are usually of static, non-immersive nature and show a strong abstraction from reality.

Level of Objectivity

Relying on objective measures instead of subjective interpretations by examiners provides more objective and comparable test results.

Potential for Ubiquitous Assessments

The increasing integration of eye tracking into everyday devices allows continuous, frequent assessments in real-life situations.

Theoretical Foundation

Imagine your brain as a bustling airport control tower. Just as air traffic controllers must constantly monitor multiple aircraft, prioritize urgent situations, and filter out irrelevant information, your brain performs a similar balancing act with attention. This complex process is governed by specialized brain networks that work together to help you focus on what's important while ignoring distractions.

How Psychologists Explain Attention

Early theories of attention were quite simple. In the 1950s, psychologist **Donald Broadbent** proposed that attention works like a filter, allowing only selected information to reach our conscious awareness while blocking out the rest. This explained why we can focus on a single conversation in a noisy room, but it had a flaw: sometimes we notice things we're not paying attention to, like hearing our name mentioned in another conversation.

Later research by **Anne Treisman** refined this idea. She suggested that attention isn't an all-or-nothing filter but more like a volume control. Unwanted information isn't completely blocked but is turned down.

Modern theories take this even further. Load Theory of Attention, developed by **Nilli Lavie**, suggests that your brain has limited processing capacity. When a task demands all your attention—like landing a plane—there's no "space" left for distractions. This is why well-designed cockpits minimize unnecessary information during critical phases of flight, helping pilots stay focused on what matters most.

Another important theory is **Multiple Resource Theory**, proposed by **Christopher Wickens**. It explains that our brains can handle multiple tasks at once—as long as they use different types of processing. For example, you can listen to music while reading because they use different mental "channels" (auditory vs. visual). But trying to read two things at once is much harder because they compete for the same visual resources.

Attention in Action: Real-World Applications

Understanding how attention works has practical applications in many fields, e.g., in aviation.

1.Pilot Training and Stress Management

Stress can narrow your focus, making it harder to notice important details. For pilots, this could mean missing critical information during an emergency. Training programs now include stress inoculation techniques to help maintain broad, flexible attention under pressure.

2. Cockpit Design and Workload Management

Modern cockpits are designed to reduce unnecessary mental load. For example, during critical phases like takeoff and landing, non-essential information is minimized or hidden, freeing up cognitive resources for the most important tasks. By minimizing extraneous load, designers help pilots focus their mental energy where it matters most.

3. Situation Awareness in Aviation

Situation awareness - the ability to perceive, understand, and anticipate what's happening around you - is crucial for pilots. It relies heavily on attention at three levels: (1) Perception, (2) Comprehension, (3) Projection.

Training programs now emphasize all three levels, helping pilots develop the attention skills needed to maintain situational awareness.

Why This Matters

Whether you're a pilot, a student, or just someone trying to stay focused in a distracting world, understanding how attention works can help you perform better. For pilots, it means safer flights and better decision-making. For the rest of us, it offers insights into how to manage our mental resources more effectively - whether we're studying, working, or just trying to stay present in a busy world.

The Brain's Attention Networks

The "Spotlight" System (Dorsal Attention Network)

Think of this as your brain's searchlight. When you deliberately focus on something - like a pilot scanning flight instruments - this network kicks into gear. It's based in areas like the intraparietal sulcus (IPS) and frontal eye fields (FEF), helping you zero in on specific information while filtering out the rest.

The "Alarm" System (Ventral Attention Network)

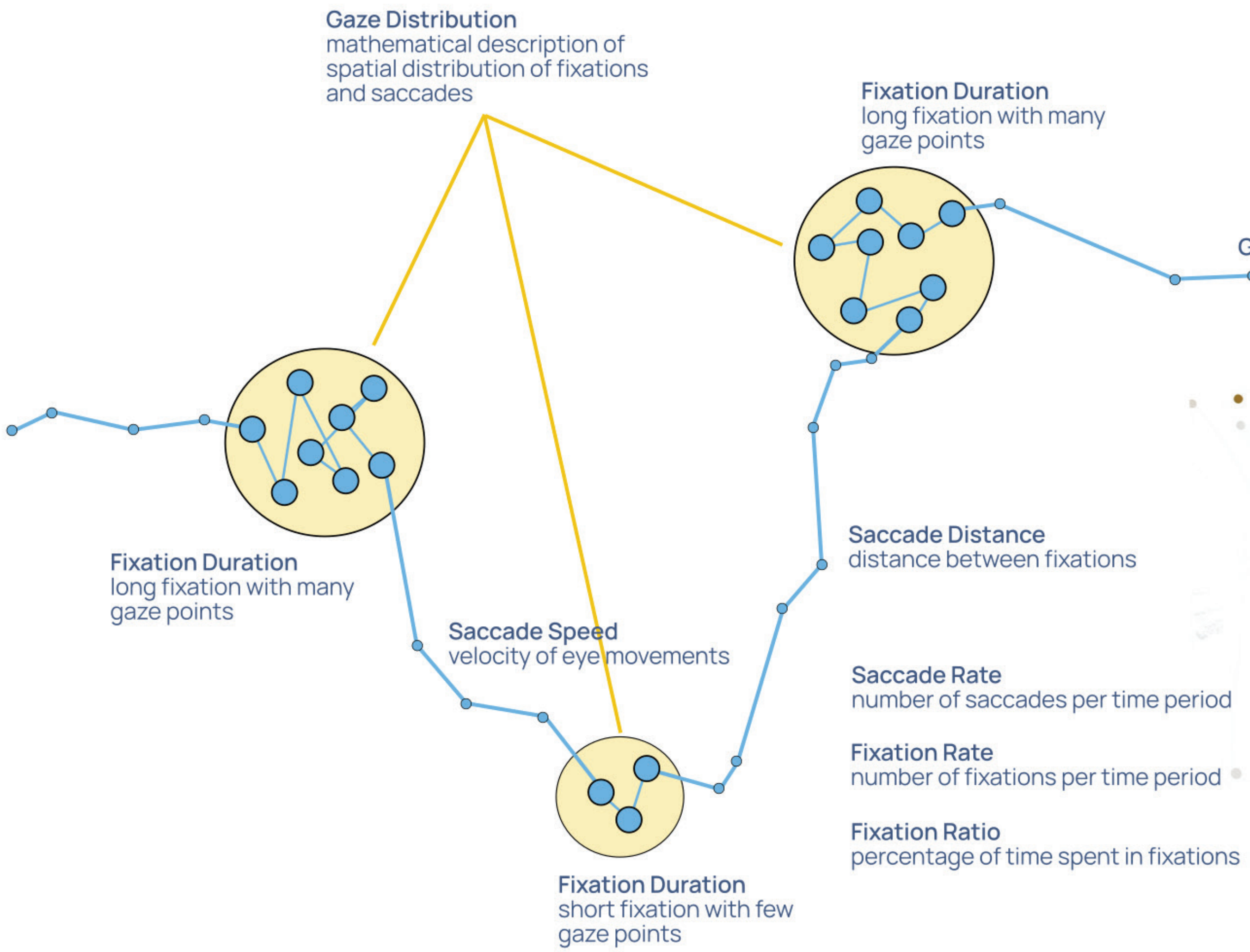
This is your brain's emergency alert system. It springs into action when something unexpected happens, like a sudden bird strike or an unexpected warning light. Based in regions like the temporoparietal junction (TPJ), it helps you quickly shift focus to potential threats.

The "Daydream" System (Default Mode Network)

When your mind wanders—perhaps during a long, uneventful flight - this network becomes active. It's suppressed when you need to concentrate, but if it's overactive, it can lead to lapses in attention.

Gaze Behavior Analytics and

Gaze behavior provides a window into cognitive processes, revealing how different aspects of visual attention are allocated based on task demands, stimuli, and individual differences. Various gaze features - such as fixation duration, saccade patterns, pupil dilation, and scanpaths - contribute uniquely to different types of attention, including selective attention, sustained attention, and switched attention.



Fixation Duration: Longer fixations on task-relevant regions indicate deeper processing, while brief fixations on distractors suggest successful filtering. Reduced dwell time per location suggests distributed processing.

Saccade Patterns: Fewer saccades to irrelevant areas reflect efficient attentional control.

Saccades Rate: Rapid shifts between different areas of interest (AOIs) indicate attentional switching.

Scanpath Complexity: More erratic gaze patterns reflect the cognitive demand of managing multiple tasks.

Different gaze features provide distinct insights into attentional mechanisms. While fixation patterns reveal selective and sustained attention, saccade dynamics and scanpath complexity are more indicative of divided attention. Pupil responses serve as a cross-cutting biomarker of cognitive load across attention types. By integrating these metrics, researchers can develop comprehensive models of attention allocation in various real-world and experimental settings.

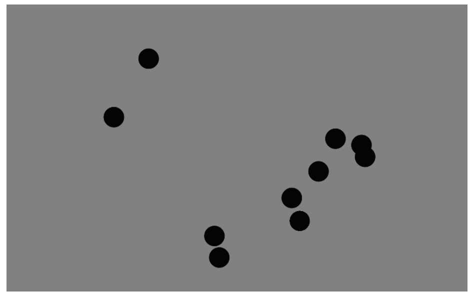
Validation & Study Results

Methodology

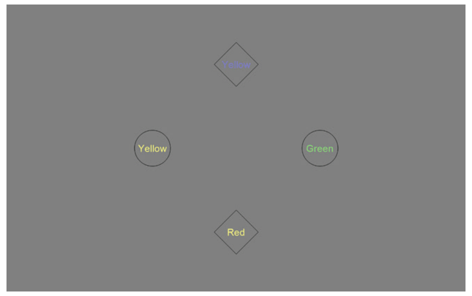
To validate the Attention Type (AT) biomarker implementation, the first study was designed to confirm the validity of the biomarker design and its features. For this purpose, the participants were given a selection of two tasks, each characteristic of one of the attentional behaviors: Focused Attention and Switched Attention. The study was carried out on a laptop screen with head-worn eye tracking glasses.

Participants: The study involved 15 participants (8 male, 7 female). Informed consent was obtained from all participants prior to the study.

Tasks: Participants performed two tasks, each characteristic of a specific attention type:



1. Focused Attention Task: Participants were instructed to focus on a specific visual stimulus (moving circle) while ignoring similar distractors. Again, after each trial, the final position had to be marked.



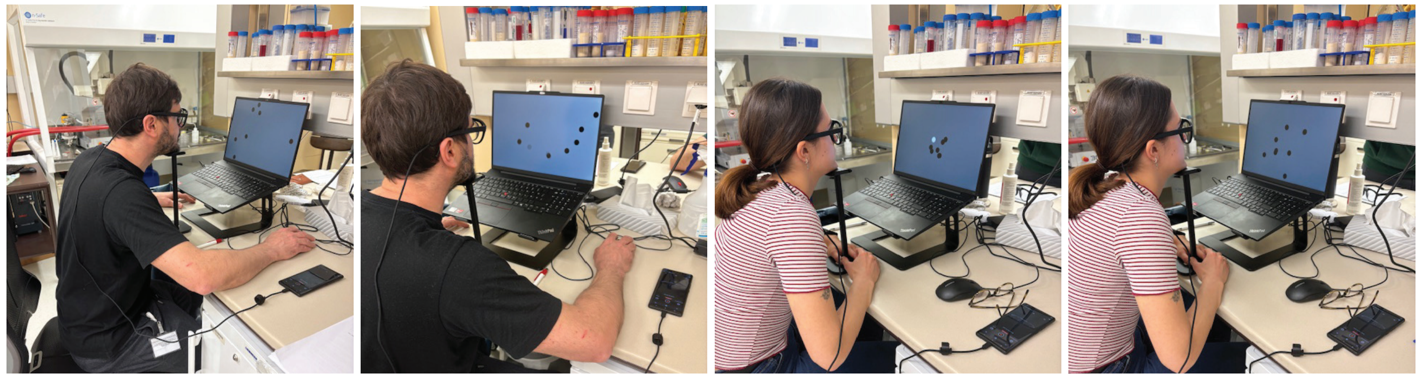
2. Switched Attention Task: Participants alternated their focus between 4 stimuli distributed across the screen. The task was to observe the stimuli and in case of changes in the geometric characteristics of these stimuli, a certain reaction had to be carried out (button press).

Eye Tracking Data Collection: Eye tracking data were collected using a Pupil Labs Neon eye tracker. The device provided raw eye tracking metrics like gaze position and pupil dilation. The other mid- and high-level features were computed using the SOMAREALITY processing pipeline.

Feature Extraction: As described in the previous sections , the following gaze behavior characteristics were used to describe attention types, with specific statistical sub-features:

- Fixation duration and distribution
- Saccade amplitude and velocity
- Gaze position variability and distribution

These features were interpreted according to their contribution to each attention type via a probability function, resulting in additional overall rule-based probability features for each attention type.



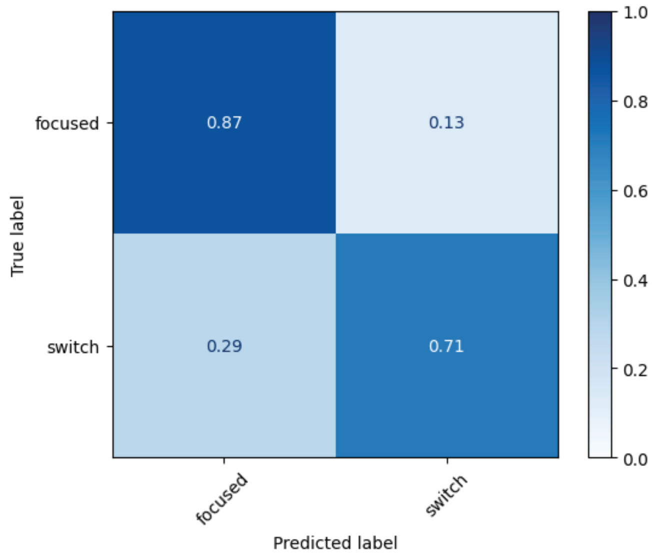
Results

Classification: A Linear Discriminant Analysis (LDA) classifier was employed to classify the attention types based on the extracted AT features. The classifier was trained with leave-one-participant-out cross-validation, where the model is trained on data from all but one participant and subsequently tested on the held-out participant (repeated for all participants) and random under sampling to balance the data, to ensure robustness and generalizability.

The SVM classifier achieved an overall accuracy of **85.2%** in classifying the two attention types. Detailed performance metrics, including precision, recall, and F1-score, are presented below:

Attention Type	Precision	Recall	F1-Score
Focused	0.93	0.87	0.90
Switched	0.55	0.71	0.62

The confusion matrix illustrates the classifier's performance across the different attention types.



Discussion

The results of this study demonstrate the potential of using eye tracking technology and machine learning techniques to classify different types of attention based on attentional behavior. The high accuracy achieved by the classifier suggests that gaze behavior features are strong indicators of attention types.

The results also show, as expected, that Focused Attention is being recognized reliably, while Switched Attention more often gets misinterpreted for focused attention.

Validation & Study Results

Methodology

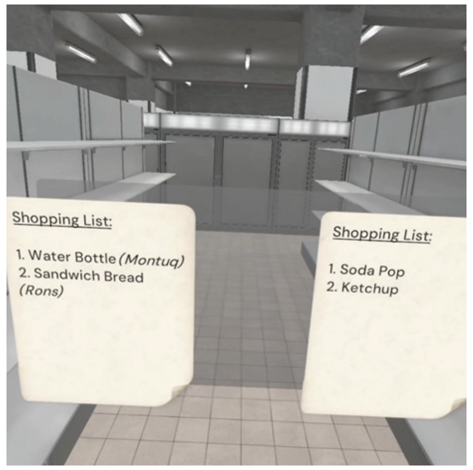
In the second study, the goal was to test and validate the ATC biomarker in a more applied, realistic application. For this purpose, the study was set up in a VR supermarket environment, performing selection and monitoring tasks.

The two types of attention were tested in the same supermarket setting using a consistent setup. Participants were first asked to memorize a list of items. Then, they were shown individual items and had to indicate whether each one was on the list. To respond, they pressed the trigger on the right controller if the item was on the list, or the left controller if it was not. Audio feedback (beeps) was provided after each response. Each of the two attention blocks consisted of four trials. The task began with easier lists (e.g., three items) and became progressively harder with each trial—adding one item at a time (e.g., three, four, five, and six items) for the focused attention tasks.

Participants: The study involved 19 participants (11 male, 8 female). Informed consent was obtained from all participants prior to the study.

Tasks: Participants performed two tasks, each characteristic of a specific attention type:

1. Focused Attention Task: This task followed the same basic format as the sustained attention task. However, the environment was visually cluttered: participants saw a supermarket aisle filled with various items and screens playing advertisements, creating a deliberately distracting setting.



2. Switched Attention Task: In this task, participants were shown two separate lists to memorize, one associated with the left side of the screen and one with the right. During the trial, a single item would appear either on the left or right side of the screen. Participants had to determine whether the item belonged to the list associated with that side. The next item would then appear on the opposite side, requiring participants to shift their attention and make eye movements back and forth across the screen.

Eye Tracking Data Collection: The experiment was presented in a VR environment using the Pico Neo headset with the SOMA AWARE insights app, and the total time for the experiment was about 15 minutes or less. There were two different blocks of trials, focused and switched, where the order was randomised for each participant.

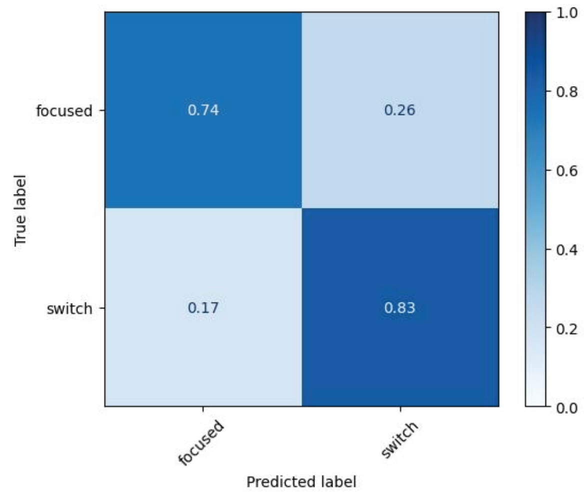
Results

Classification: Again, a Linear Discriminant Analysis (LDA) classifier was used for the classification of the attention types. The classifier was trained with leave-one-participant-out cross-validation, where the model is trained on data from all but one participant and subsequently tested on the held-out participant (repeated for all participants) and random under sampling to balance the data, to ensure robustness and generalizability.

The Random Forest classifier achieved an overall accuracy of **78.4%** in classifying the two attention types. Detailed performance metrics, including precision, recall, and F1-score, are presented below:

Attention Type	Precision	Recall	F1-Score
Focused	0.81	0.74	0.77
Switched	0.76	0.83	0.79

The confusion matrix illustrates the classifier's performance across the different attention types.



Discussion

Similar to the previous study, the results of this study highlight the strong potential of combining eye-tracking technology with machine learning techniques to distinguish between different types of attention based on gaze behavior. Compared to the earlier study, the tasks and overall design in the current study appear to have been better optimized to evoke the expected patterns of visual attention.

In this experiment, the Switched Attention type can be more easily separated from focused attention due to the more explicit differences in observable behavior.

Use-Case Scenarios

Aviation and Pilot Training

Classifying pilots' attention types during flight simulations can significantly improve **training outcomes and safety**. Instructors can identify when pilots focus on critical instruments during landing (selective attention), monitor fixation duration to detect vigilance decrement during long-haul flights (sustained attention), and assess gaze transitions between instruments and external visuals to evaluate multitasking efficiency (divided attention). These insights allow for the **optimization of training programs and cockpit design to reduce errors and enhance performance**.

Healthcare and Surgical Training

Analyzing surgeons' attention allocation during procedures can lead to **improved precision and reduced fatigue.** Attention type analytics helps ensure surgeons maintain focus on the surgical field while ignoring distractions (selective attention), detect fatigue-related attention lapses during prolonged surgeries (sustained attention), and evaluate gaze shifts between monitors, instruments, and patient vitals (divided attention). This data can be used to **enhance surgical training and reduce medical errors, ultimately improving patient outcomes.**

Automotive and Driver Monitoring

Real-time classification of drivers' attention types can play a crucial role in **preventing accidents.** By verifying that drivers focus on the road rather than distractions like phones or billboards (selective attention), detecting drowsiness through fixation patterns (sustained attention), and assessing gaze distribution between mirrors, dashboards, and traffic (divided attention), adaptive safety systems can provide timely alerts or even autonomous intervention when necessary. This technology has the potential to significantly **improve road safety**.

Education and E-Learning

Personalizing learning experiences based on students' attention patterns can greatly **enhance educational outcomes**. Eye tracking can identify when students focus on key concepts versus distractions like social media (selective attention), measure engagement with course materials over time (sustained attention), and evaluate multitasking between lecture slides and notes (divided attention). These insights enable instructors to **improve instructional design and ultimately boost student performance**.

Marketing and Consumer Behavior

Classifying attention types can help **optimize advertising and product placement strategies**. By identifying which elements, such as logos or calls-to-action, capture focus (selective attention), measuring engagement duration with ads or packaging (sustained attention), and assessing gaze distribution across competing stimuli like shelf displays (divided attention), marketers can increase conversion rates and return on investment. This data-driven approach allows for more effective and targeted marketing campaigns.

Sports Performance Analysis

Enhancing athletes' **focus and decision-making** through attention classification can lead to improved performance. Tracking gaze on opponents versus distractions like crowd noise (selective attention), monitoring fixation stability during high-pressure moments (sustained attention), and evaluating gaze shifts between teammates, opponents, and field markers (divided attention) provides valuable insights. Coaches can use this information to **refine training regimens and improve in-game performance**.

Human-Computer Interaction (HCI)

Adapting interfaces based on users' attention types can significantly enhance **usability and productivity**. By prioritizing UI elements that attract focus (selective attention), adjusting content complexity based on engagement (sustained attention), and optimizing multitasking workflows like split-screen layouts (divided attention), designers can create more intuitive and efficient interfaces. This user-centered approach leads to **better user experiences and increased productivity**.

Mental Health and Cognitive Assessment

Detecting attention deficits in clinical settings can aid in **diagnosis and personalized treatment plans**. Identifying difficulties in filtering distractions (selective attention), measuring vigilance in tasks requiring prolonged focus (sustained attention), and assessing multitasking impairments (divided attention) provides valuable data for mental health professionals. This objective measurement can lead to **more accurate diagnoses and tailored interventions for conditions like ADHD or post-concussion syndrome**.

Workplace Productivity

Optimizing office environments based on employees' attention patterns can boost **productivity and well-being.** Reducing visual and auditory distractions in open-plan offices (selective attention), designing break schedules to combat fatigue (sustained attention), and evaluating multitasking efficiency in collaborative workspaces (divided attention) helps create more effective work environments. These insights allow organizations to implement changes that **enhance employee performance and satisfaction**.

Gaming and VR/AR Applications

Enhancing immersive experiences through attention-aware design can greatly **improve user engagement**. Directing gaze to key narrative elements (selective attention), adapting difficulty based on engagement levels (sustained attention), and balancing visual and auditory stimuli in VR environments (divided attention) creates more compelling and comfortable experiences. This approach **can reduce motion sickness and increase user satisfaction in gaming and virtual reality applications**.

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

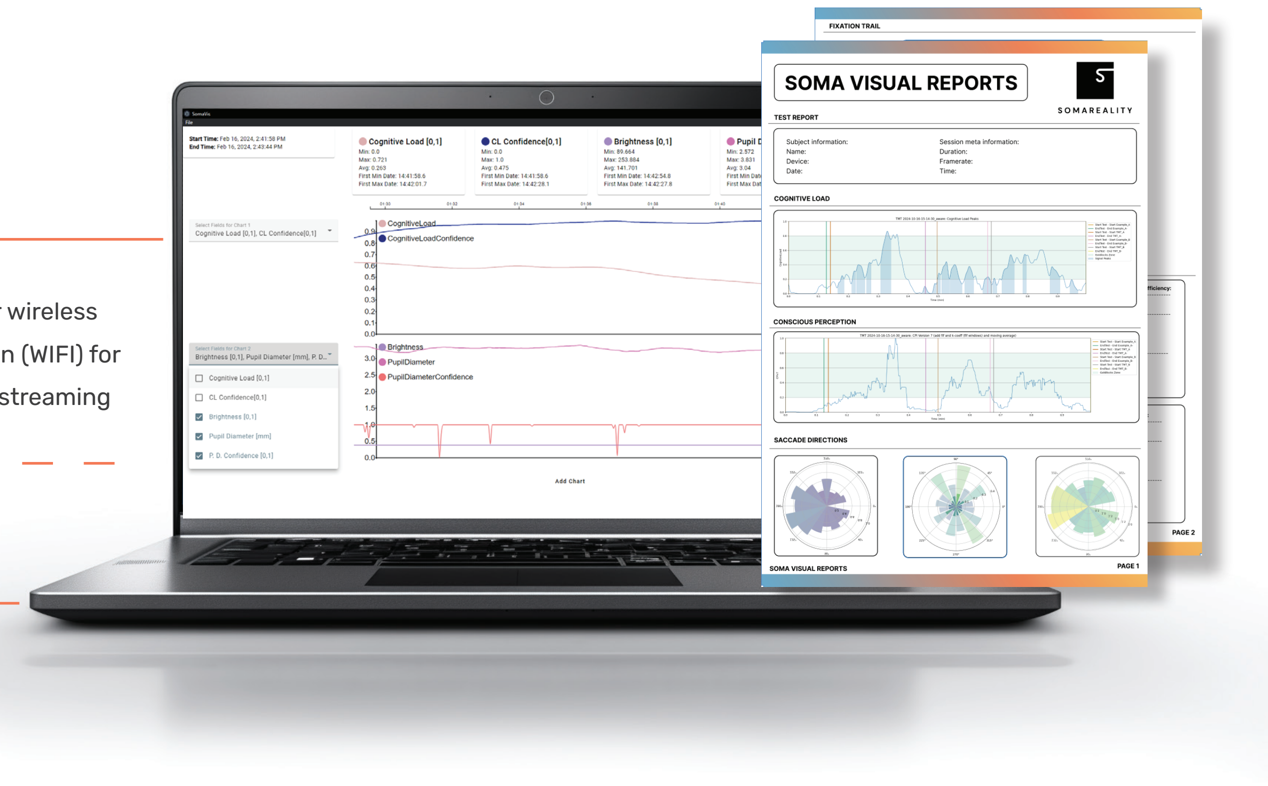
open access to relevant data streams

- 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)

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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