SWAY

The Science Behind Sway

How Continuous Multimodal Sensing Enables Flow, Focus, and Mental Resilience

Introduction

In a world defined by digital distraction, rising stress, and cognitive overload, the ability to sustain focus and maintain mental well-being has never been more valuable - or more elusive. While the demand for productivity tools is booming, there's a parallel surge in interest for recovery and stress management solutions, as seen in the widespread adoption of products like the WHOOP Band and Oura Ring. Yet despite these tools, most knowledge workers continue to struggle with maintaining attention, recovering from mental fatigue, and entering deep states of immersive work.

The need for science-backed systems that not only enhance focus but also support long-term mental clarity and resilience is more urgent than ever.

At Sway, we propose a new path forward. By continuously monitoring key neurological and physiological signals - electroencephalography (EEG), electrooculography (EOG), and photoplethysmography (PPG) - and analyzing their trends over time, we can model cognitive state in real time with unprecedented depth and accuracy.

Sway's approach is grounded in six scientific pillars that together form the foundation of our cognitive state modeling system. By integrating all-day wearable technology with multiple biosignal modalities, we unlock a new frontier in understanding focus, flow, fatigue, and mental performance. What follows is a breakdown of each pillar, the science behind it, and how they interconnect to support our central hypothesis: that a comfortable, multi-sensor wearable can continuously monitor brain and body signals to optimize cognitive performance and well-being.

The Six Pillars

The science behind Sway is grounded in six key pillars, each representing a core area of research that informs our hypothesis and product design:

1. **EEG, EOG, and PPG** – Leveraging brain, eye, and heart signals
2. **Flow Modeling** – Understanding short-term cognitive performance
3. **Fatigue, Stress, Rest, and Recovery** – Capturing short-term cognitive recovery and resilience
4. **Trends and Baselines** – Modeling long-term balance, growth, and cognitive health trajectories
5. **Sensor Fusion** – Integrating multiple signals for greater depth and accuracy
6. **Interpretation, Processing, and Modeling** – Building a robust, all-day wearable system with meaningful insights

Together, these pillars support the development of the Sway S1 smart glasses and provide the scientific framework for real-time cognitive modeling. In the sections that follow, we explore each pillar in more depth – highlighting foundational concepts, relevant literature, and how each area directly contributes to our system's capabilities.

EEG, EOG, and PPG: Leveraging Brain, Eye, and Heart Signals

Sway's device measures electroencephalography (EEG) for brain waves, electrooculography (EOG) for eye movement/blinks, and photoplethysmography (PPG) for heart rate and variability. Each of these biometric signals provides a window into your cognitive and emotional state. Research shows that brainwave patterns correlate with focus and stress levels, heart rate variability reflects mental effort, resilience, and restfulness, and eye blinks/behaviors indicate alertness or mind-wandering [1][2]. By capturing all three, we obtain a more holistic picture of the user's state than any single signal alone.

EEG measures the brain's electrical activity, and this activity can be broken up across different frequency bands, each linked to specific cognitive states. For example, beta waves (12-30 Hz) are associated with focused attention and mental effort, while slower theta waves (4-8 Hz) are linked to creativity, memory, and internal thought. The theta/beta ratio (TBR) is often used as a marker of attentional regulation – too high may indicate daydreaming or distractibility, but too low may suggest overstimulation or stress. Recent findings suggest that optimal cognitive performance occurs within a balanced TBR range, where enough theta supports flow and creative insight, and beta maintains directed focus without tipping into mental strain [3][4].

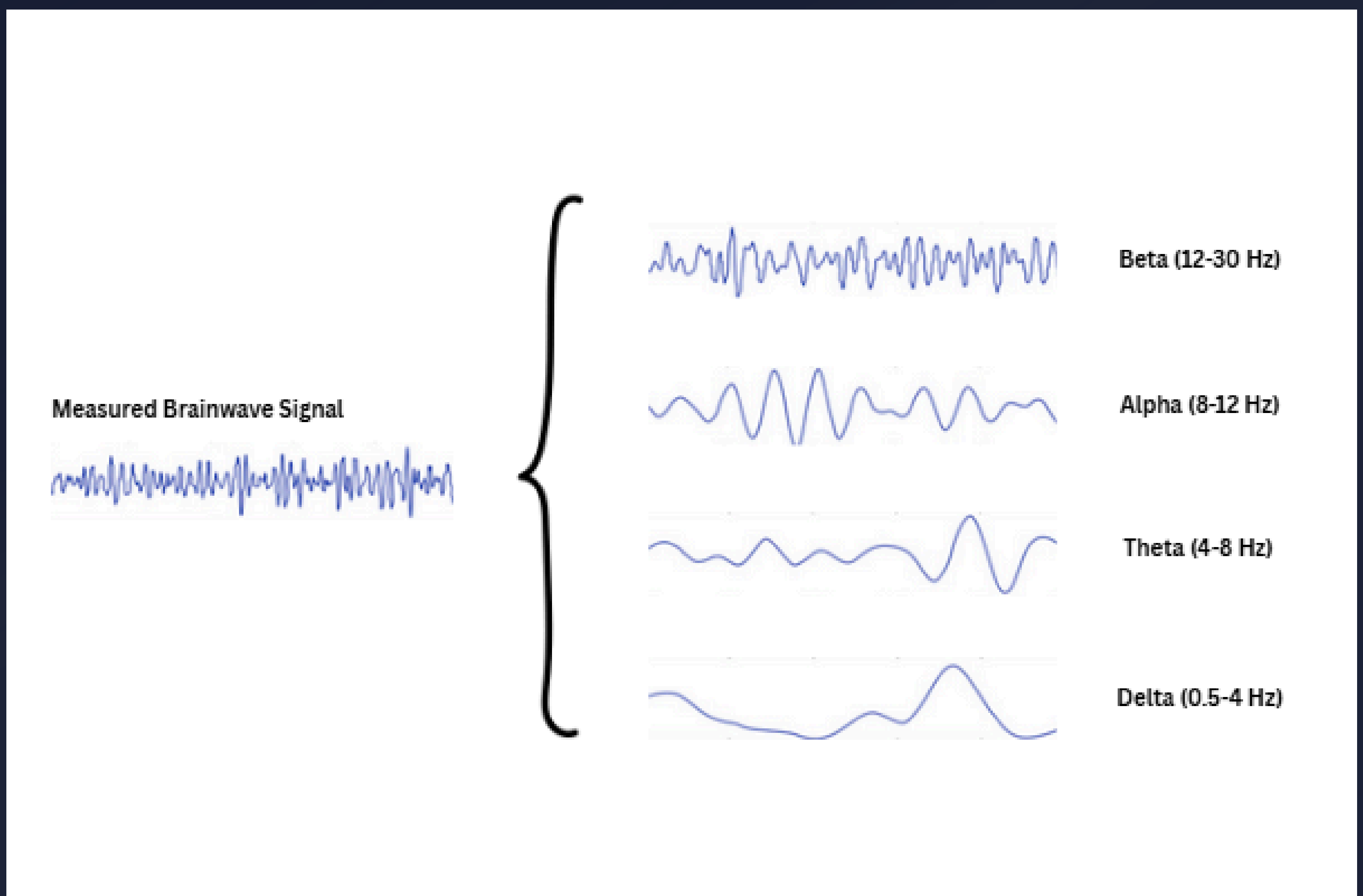


Figure 1: Human Brainwave Bands

EOG from tiny sensors around the eyes tracks blinks and eye movements – frequent blinking has been tied to mind-wandering and dopaminergic activity [5], while long slow blinks can signal drowsiness, and lower blink rates can correlate with sustained attention. PPG from an optical pulse sensor in the glasses frame around the nose measures heart beats and variability. Heart Rate Variability (HRV) is especially informative: high HRV (indicating strong parasympathetic "rest and digest" tone) has been consistently associated with better cognitive function and executive control, whereas low HRV (sympathetic dominance) accompanies stress and worse performance [2]. By monitoring the brain, heart, and eyes together, Sway taps into the interconnected neurological and cardiovascular systems that underly focus and fatigue. Traditional wearables might track

Figure 2: Multimodal Sensors in Sway S1s

heart rate or sleep, but they miss the brain and eye activity where much of "cognitive state" throughout the day resides. By integrating EEG, EOG, and PPG, we can detect subtle changes: for example, Sway's glasses can potentially sense when you shift into a flow state (via blink patterns and EEG characteristics), when your mind starts to wander, and when you're under stress (via decreased HRV and elevated high-frequency EEG activity). This pillar establishes the physiological basis – the raw signals – needed to model complex states like flow or fatigue. This leads into the next pillar: using these signals to identify when you're "in the zone" versus distracted.

Flow Modeling: Recognizing the "Zone" and Deep Focus States

Flow is the highly productive mental state of being "in the zone" – fully absorbed in a task, performing at your best with energized focus and enjoyment. Sway's hypothesis argues that flow states have identifiable physiological signatures that we can model using wearable sensors. Scientific studies of flow (from e-sports to musical performance) reveal consistent patterns: brainwaves shift toward moderate-to-high alpha and theta, slightly reduced beta, stable, low-to-mid-range heart rhythms, and reduced erratic eye movement (blinks and gaze) [6]. In flow, the mind is alert but calm – not stressed, not sleepy. By modeling these patterns, we aim to detect when a user enters or leaves flow, and the quality of that flow, enabling feedback to help them achieve flow more often.

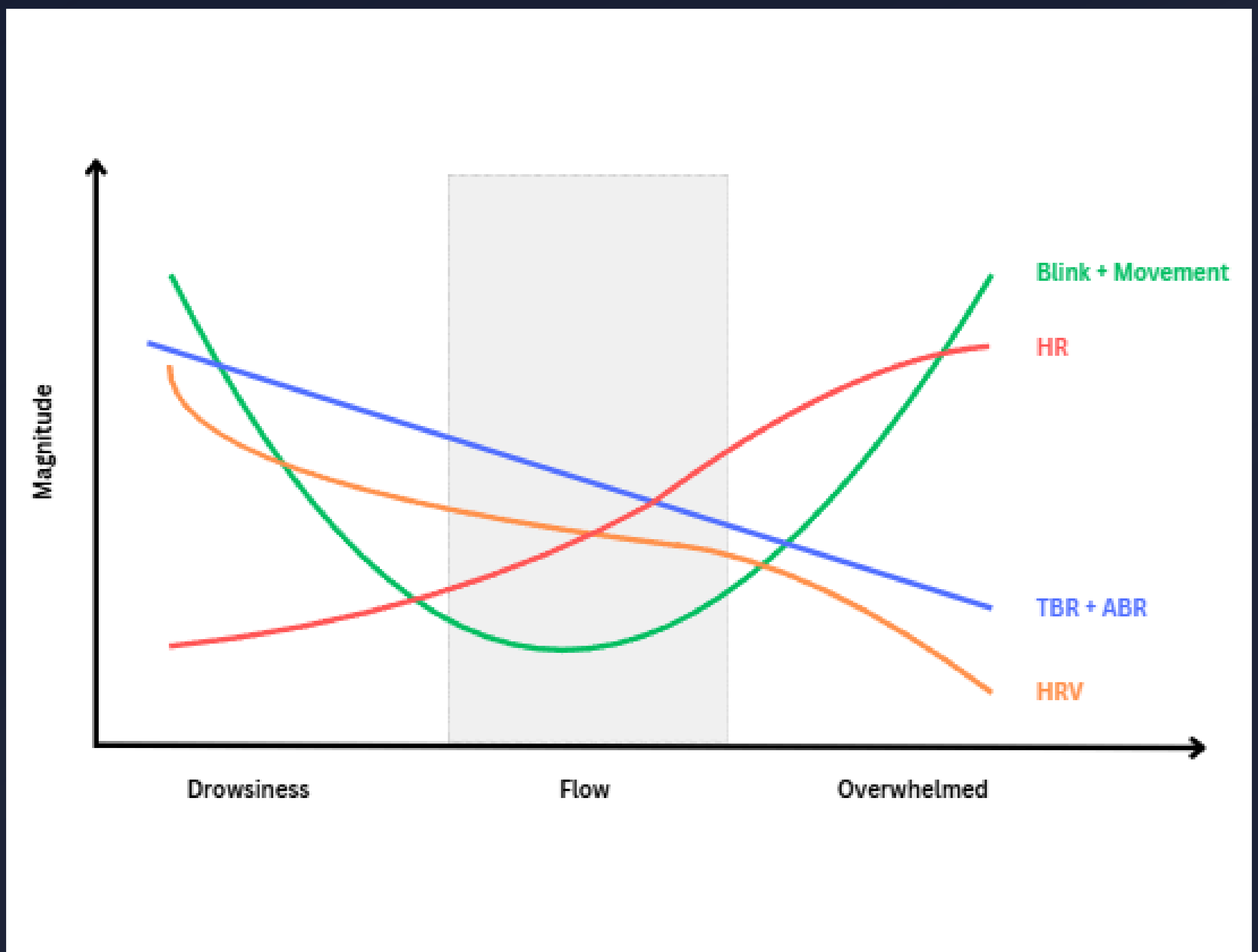


Figure 3: Signal Modalities and Flow Graph

Decades of neuroscience research have begun to quantify flow. EEG studies show that during flow, the brain finds an optimal balance of activation: theta waves increase, reflecting deep internal concentration, alpha waves also elevate modestly, signifying that extraneous distractions are being inhibited. Meanwhile, beta increases slightly from boredom, but remains lower than a frustrated, stressed, and overwhelmed state. This combination – increased theta coupled with moderate alpha and low-moderate beta – differentiates flow from boredom (too little activation) and from stress/overload (excess high-frequency beta and suppressed alpha). In one experiment, participants performing a challenging mental arithmetic task showed the highest self-reported flow when their EEG exhibited exactly this theta/alpha/beta profile, compared to low-engagement or overwhelm [4].

Complementing EEG, heart rate variability tends to be in a Goldilocks zone during flow: higher than during anxious stress (where HRV plummets) but not as high as during meditative rest – this suggests a state of relaxed alertness. A pilot study of pianists in flow found their autonomic nervous system maintained a relaxed alertness – their HRV indicated focus without fight-or-flight activation [7]. Similarly, athletes and gamers in flow often have steady heart rates and quick vagal recovery, reflecting a state of energized calm. Eye behavior in flow also changes: people often exhibit fewer blinks and smooth, uninterrupted gaze patterns when fully immersed.

By modeling flow, Sway seeks to give users a tangible metric ("Flow Score") for quality of focus. The science suggests flow is not mystical – it's a reproducible psychophysiological state. Sway's multi-sensor measurements will look for the telltale signs: a sweet spot of EEG rhythms, balanced HRV, and steady eye engagement. This pillar ties back to the first: we use those raw EEG/EOG/PPG signals to identify something high-level and valuable – when you're performing at your cognitive best. It also connects forward to the next pillars: understanding flow isn't enough without also tracking the flipside (stress and fatigue) and personalizing to individual baselines.

Fatigue, Stress, and Recovery: Balancing Performance with Rest

High performance cannot be sustained without adequate rest and stress management. Another pillar of Sway's science is tracking mental fatigue and stress levels, and highlighting the need for recovery. Just as important as identifying flow is recognizing when the brain and body are strained or exhausted. Chronic stress and fatigue leave distinct fingerprints on our biosignals – HRV tends to decrease, EEG patterns shift (e.g., alpha waves slow down, theta spikes during drowsiness), and even baseline metrics like one's peak alpha frequency can drift with burnout [8][9]. By monitoring these indicators, Sway can alert users to take breaks, practice mindfulness, or get sleep, effectively closing the loop between peak focus and restorative rest.

Mental fatigue often manifests as a reduction in complexity of physiological signals. For instance, heart rate variability loses its variability – a fatigued individual shows a monotonous heart rhythm dominated by sympathetic (stress) drive. One study in chronic fatigue syndrome patients found that the more severe the fatigue, the lower all major HRV indices, indicating an autonomic imbalance with overactive fight-or-flight response [8]. In fact, fatigue scores correlated negatively with nearly every HRV measure (and positively with the stress-index LF/HF ratio) – essentially exhaustion mirrors low HRV. Sway's continuous HRV tracking can pick up on these trends, notifying users when their autonomic state suggests extreme fatigue before they subjectively crash.

In the brain, prolonged stress or burnout is linked to shifts in EEG. Research on burnout patients has shown alterations in the alpha band – some report a slowing of the individual alpha frequency and others a reduction in alpha power, alongside elevated theta, reflecting impaired cognitive efficiency and possibly mild neural instability [9][10]. High stress can also elevate high-beta "fast" activity (rumination, anxiety) or conversely, after long hours, lead to bouts of theta bursts (mind-wandering, micro-sleeps). Drowsiness is a clear example: as one becomes tired, alpha waves slow and blend into theta, and eventually theta dominates as you approach sleep onset [10]. Sway's EEG could catch early drowsy signatures – e.g., during a late-night study session – and advise a break. In addition to noticing and flagging when things are going "wrong", Sway can display to users the total time spent in different states throughout the day to influence decisions regarding rest, recovery, and performance. For example, if elevated beta power has dominated throughout the entire day, the system may suggest a practice to reduce beta, increase alpha and theta, such as a relaxed reading or meditation session.

Moreover, recovery practices (relaxation, meditation) produce measurable improvements in these signals. For example, stress reduction techniques like slow breathing or meditation can acutely boost HRV and shift EEG toward a calm-alpha state [11]. Over time, such practices raise baseline vagal tone and cognitive resilience. Sway's aim is not only to warn of fatigue or stress but also to validate recovery: the user can see their metrics rebound (higher HRV, normalized brain patterns) after a good night's sleep or a vacation, reinforcing healthy habits.

We live in an age of burnout. Recognizing when you're pushing past healthy limits is crucial. This pillar ensures that Sway's recommendations aren't just about working harder or finding flow, but equally about resting smarter. By quantifying stress and fatigue, Sway provides an objective check-engine light for your brain. This pillar flows from the previous: after intense flow, one needs recovery to avoid diminishing returns. It also sets up the next pillar – understanding personal baselines, because "high stress" for one person might be normal for another; individualized trends are key.

Trends and Baselines: Personalization Through Longitudinal Data

No two individuals have identical biometrics, and even the same person fluctuates day to day. Thus, Sway's science emphasizes establishing personal baselines and tracking trends over time. We don't just compare you to some generic population average – we compare you to you: your past week, month, or year. This pillar draws on research showing significant inter- and intra-individual variability in signals like EEG and HRV [12]. By accounting for these variations, Sway can detect meaningful changes (e.g., a decline in your focus metrics might be more important than the absolute level relative to someone else). It also leverages population insights (like age norms for brainwave speed) to provide context to your data.

One striking example comes from EEG: individual alpha peak frequency (IAF) – essentially the frequency of your dominant alpha brain rhythm – is a highly personal trait that correlates with cognitive processing speed. It tends to slow with age and can differ by up to 2–3 Hz between healthy individuals of the same age [12]. A large study in 2016 ("Characterizing Population EEG Dynamics Throughout Adulthood") mapped these differences and found a gradual slowing of alpha frequency and changes in power distribution as people age, especially after middle age [12]. This means a 60-year-old's "ideal" alpha might be naturally lower than a 20-year-old's. Sway's analytics take such baseline shifts into account when interpreting whether a given alpha level is concerning or normal.

Moreover, day-to-day variability in metrics can signal changes in mental state. A 2023 study had individuals use a mobile EEG daily and found that fluctuations in their alpha band characteristics correlated with anxiety levels [13]. On more anxious days, participants' alpha rhythms showed different patterns (e.g., slight frequency shifts or amplitude changes) compared to calmer days. This demonstrates that even your own baseline isn't static – it oscillates with mood, stress, sleep quality, etc. Therefore, Sway doesn't treat a single day's reading in isolation; it looks at short-term trends. If your focus-related signals have been steadily improving, one off-day might be just a blip. Conversely, a slow decline over weeks in your "focus capacity" metric would be flagged.

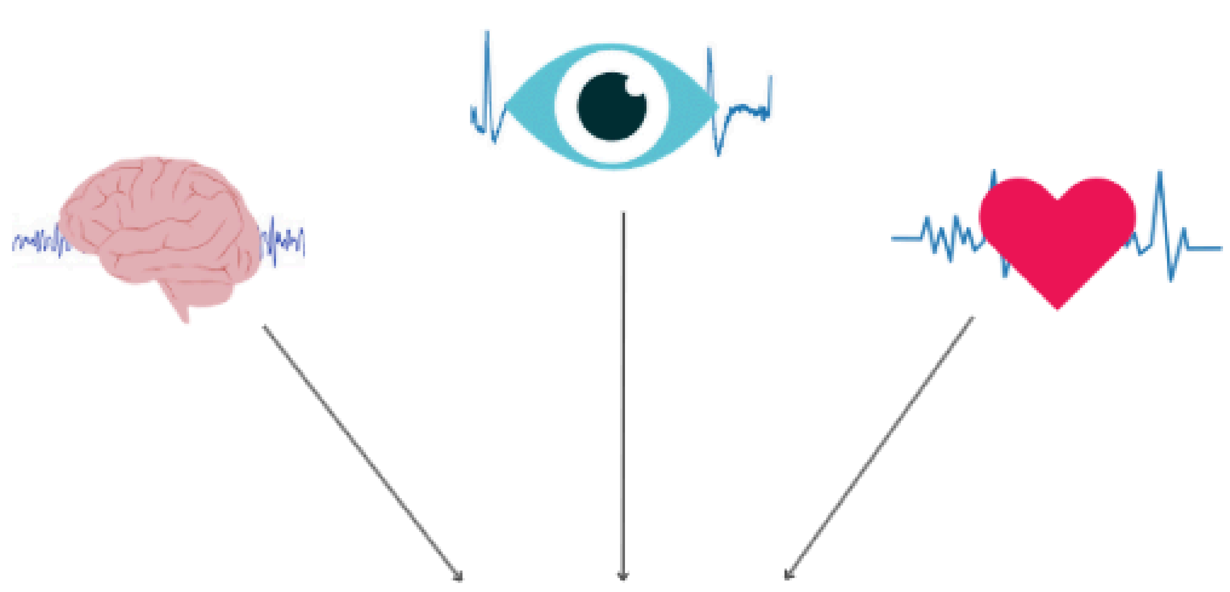
Population baselines also help identify outliers that merit attention. For instance, research has linked unusually low alpha power or slow alpha frequency at rest to higher depressive scores and anxiety [14]. If Sway notices that a user's resting brain patterns consistently deviate from healthy norms (taking age into account), it could suggest they might benefit from stress-reduction strategies or even a professional evaluation – a data-driven nudge for mental well-being.

This pillar is all about personalization and context. It prevents overreacting to normal variability ("My focus score dropped 5 points today!" might mean nothing if it's within your usual range) and ensures significant shifts are recognized. Over time, Sway essentially builds a "digital twin" of your cognitive patterns – knowing what your good days look like, what your tired days look like, and how external factors (season, workload, etc.) affect you. This empowers truly personalized coaching. This ties into the next pillar: sensor fusion and modeling, which enable this robust long-term baseline data.

Sensor Fusion: Combining Modalities for a Complete Picture

The whole is greater than the sum of its parts. Sway's multi-sensor approach isn't just for bragging rights – it's rooted in the principle of sensor fusion, where data from different physiological streams are integrated to yield more accurate and robust insights. Each sensor (brain, heart, eye) has its strengths and weaknesses. By fusing them, we compensate for individual limitations and noise, achieving a far more reliable assessment of cognitive states [15]. In practical terms, this means fewer false alarms and missed events – for example, if EEG alone is ambiguous about whether you're distracted or just momentarily reflective, your heart rate and blink pattern can tip the scale.

Research in human factors and neuroergonomics has repeatedly shown that multimodal models outperform unimodal ones for mental state detection. A 2024 study directly compared six modalities (EEG, fNIRS, EOG, eye tracking, ECG, PPG) during various cognitive tasks and found that each modality was sensitive to workload in different ways [15]. Crucially, it concluded that combining brain signals with peripheral signals provided the most consistent and rich assessment of mental workload across individuals. For instance, EEG might quickly register a lapse in attention, while HRV might indicate rising stress even if attention appears steady; if both change together, confidence is high that the person is overloaded.



Time	Beta	Alpha	RMSSD	BR	...
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Figure 4: Multimodal Sensor Fusion

From a machine learning perspective, sensor fusion can occur at data level or decision level. Sway's approach uses both: we synchronize the time-series from EEG, EOG, PPG and extract features that span modalities (e.g. an index that might be "high beta brainwave + high heart rate = agitation"). We also consider independent classifications (maybe an EEG-based focus score and an HRV-based stress score) and then combine those scores intelligently. This hybrid fusion architecture is informed by studies like one from 2021 which proposed algorithms to predict the optimal fusion strategy for different contexts, noting that a well-chosen fusion scheme markedly improved accuracy in detecting cognitive load across multiple [16].

The end goal is trustworthy insights. We don't want to tell a user "you're unfocused" when in fact it was just a momentary artifact on EEG. Fusing EOG with EEG helps mitigate that – we can distinguish true neural theta vs. eye-blink noise. Similarly, PPG helps distinguish cognitive stress from physical movement or excitement. In essence, sensor fusion improves signal fidelity and context awareness. This pillar is the glue that holds together all the signals Sway gathers, ensuring the device's feedback is based on a comprehensive understanding of your physiological state rather than a siloed view.

Interpretation and Modeling: From Raw Data to Actionable Insights

Collecting data is only half the battle; making sense of it is the other. This pillar covers Sway's use of advanced signal processing, artifact removal, and machine learning modeling to interpret the sensor data into meaningful cognitive metrics. We employ techniques from cutting-edge research to ensure that what we measure is truly brain/heart/eye activity of interest (not noise or movement), and to translate complex biosignals into simple, useful feedback. This includes everything from removing motion artifacts in EEG, to using features like Hjorth parameters or connectivity metrics for better classification, to deploying on-device AI models (TinyML) so that analysis is fast and privacy-preserving.

Artifact removal is crucial for wearable EEG/PPG. Sway leverages methods such as Adaptive Signal Reconstruction (ASR) and Independent Component Analysis (ICA) to filter out noise. For example, one study managed to extract clean EEG signals from data recorded during extreme movement (skateboarding) by using ASR+ICA, effectively "shredding" artifacts while keeping neural info [17]. We apply similar methods so that physical activities (walking, turning your head) don't completely swamp the cognitive signals.

Thus, before modeling, all data passes through a standardized preprocessing pipeline: notch and bandpass filtering to isolate meaningful frequency bands, amplitude threshold filtering, followed by advanced artifact rejection using ASR, ICA, and machine learning. These techniques remove transient noise, motion, and eye/muscle artifacts while preserving the underlying neural and physiological signals needed for accurate analysis.

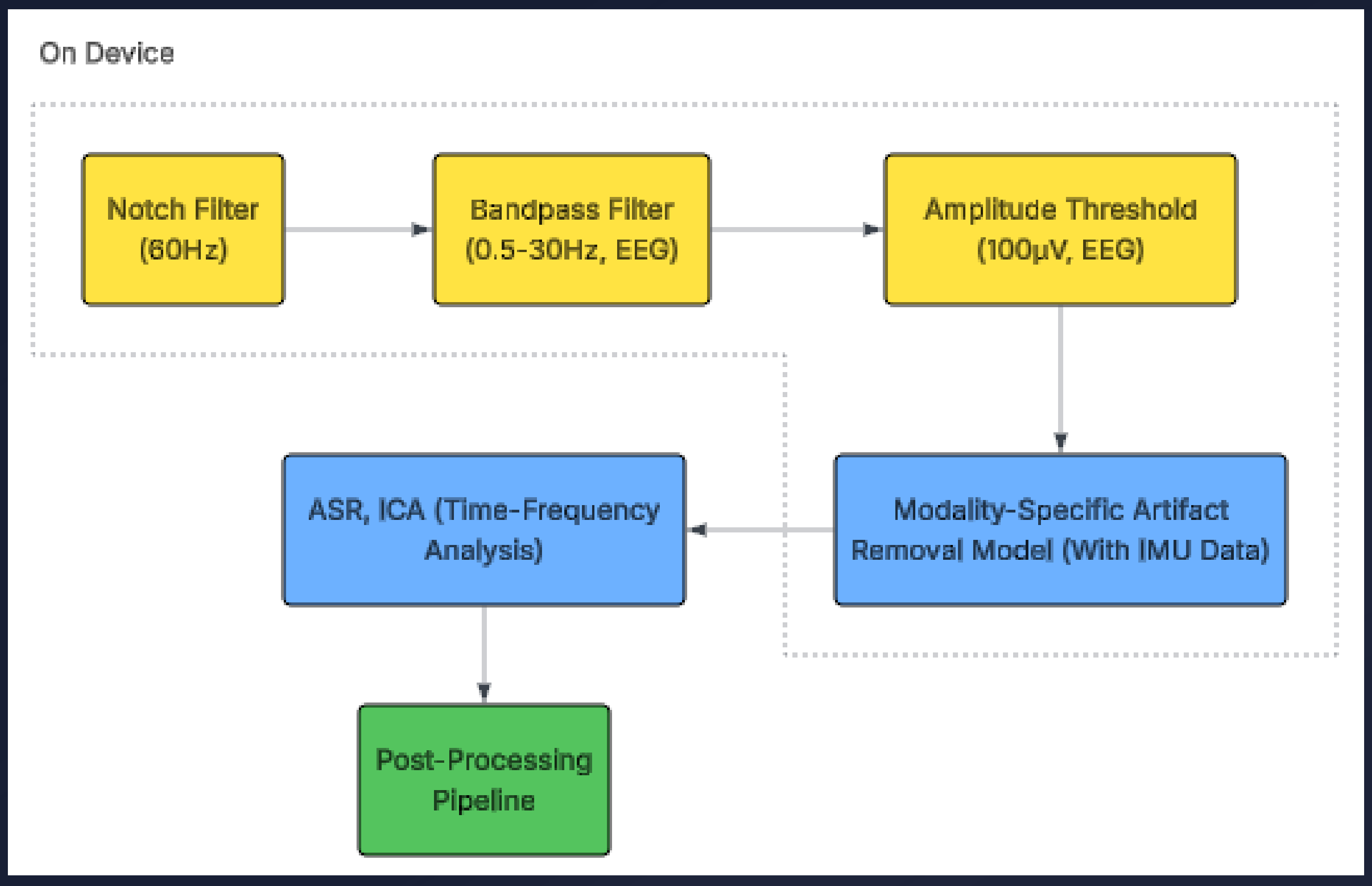

Figure 5: Signal Processing and Artifact Removal Pipeline

On the modeling side, Sway's algorithms draw from established biomarkers and machine learning features. We incorporate classical features discussed previously like bandpower magnitudes, frequencies, ratios (e.g., theta/beta, which we know correlates with attention), Hjorth parameters (mobility and complexity of EEG – proven useful in EEG analysis [18]), blink rates and amplitudes, and heart rate dynamics (like RMSSD for short-term HRV).

Additionally, connectivity measures (how different brain regions' signals correlate) and entropy measures can enrich the detection of states like flow or fatigue that involve network-level changes [19].

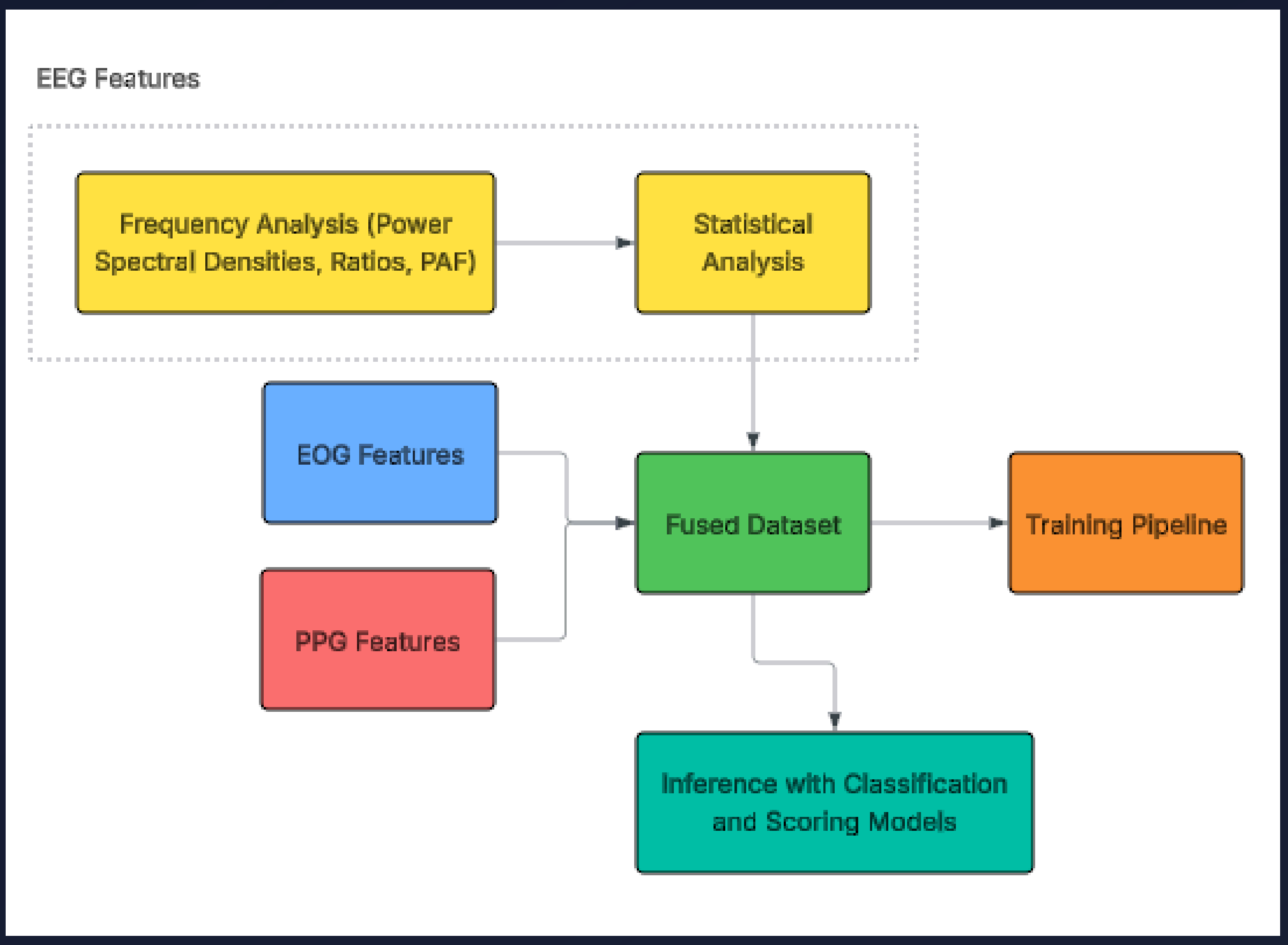

Figure 6: Feature Extraction and Machine Learning Pipeline

Edge AI is another component in Sway's architecture, enabling real-time artifact detection and filtering directly on device. Rather than running full cognitive state inference at the edge, low-power models identify and discard segments contaminated by movement, signal loss, or poor contact. This preprocessing step ensures that only high-quality data is transmitted for further analysis. More computationally intensive tasks in the preprocessing pipeline – such as Independent Component Analysis (ICA), Artifact Subspace Reconstruction (ASR), and time-frequency decomposition – are performed server-side, where richer contextual and temporal models can be applied. This division of labor enables passive, all-day wear without draining device resources, while still supporting high-fidelity signal processing and robust insight generation.

Together, these processes ensure that Sway's cognitive insights are built on a foundation of clean, interpretable, and physiologically meaningful data.

From real-time artifact detection at the edge to advanced offline processing using validated methods like ASR, ICA, and time-frequency analysis, the system maintains a high standard of signal quality throughout the pipeline. By extracting features directly tied to cognitive states – such as spectral ratios, HRV indices, and neural complexity – we preserve scientific rigor while delivering metrics that are responsive, trustworthy, and grounded in decades of research. This interpretive layer is what transforms raw biosignals into clear feedback, closing the loop between sensing and actionable mental performance insights.

Connecting it All

These six pillars form a cohesive framework. EEG, EOG, PPG provide the raw physiological channels; Flow Modeling and Fatigue/Stress Monitoring define the key states and outcomes we care about; Trends & Baselines personalize the interpretation; Sensor Fusion ensures we use all data optimally; and Interpretation & Modeling turns signals into real-time insights. Together, they support Sway's core hypothesis: that by wearing a comfortable, multi-sensor device throughout the day, users can objectively understand and improve their mental states in ways never before possible. Without explicitly saying it, the science justifies Sway's existence – it fills the gap left by single-sensor gadgets and short lab tests, enabling continuous brain-body sensing in everyday life.

Ultimately, Sway empowers the individual with self-knowledge. The union of these pillars means you can trust the device to alert you when you need a break, cheer you on when you're in flow, and guide you toward habits that enhance your cognitive performance and well-being. This is the future Sway is working to create – where decades of laboratory findings about human physiology and performance are accessible to you, on your terms, to help you live and work at your best.

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