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Don't lower your expectations to meet your performance.
Raise your level of performance to meet your expectations.

….. Ralph Marston

Abstract

Peak performance in domains such as sports, academics, and high-stakes professions is often underpinned by distinct neuro-physiological patterns. Quantitative Electroencephalography (QEEG) has emerged as a pivotal tool in identifying these patterns, offering insights into the neural correlates of elite performance. This paper synthesizes experiment – based studies on QEEG findings related to peak performers, highlighting consistent markers such as elevated Sensorimotor Rhythm (SMR), frontal midline theta activity, and specific coherence patterns. The implications of these findings for performance enhancement and neuro-feedback interventions are discussed. The paper explores neurophysiological underpinnings associated with achieving peak performance, using quantitative electroencephalography (qEEG) as a primary tool for analysis. It discusses how specific brain wave patterns correlate with optimal functioning in various domains, including sports, academics, and artistic endeavors. Authors emphasize that understanding these signatures can lead to enhanced training methods and performance outcomes. The paper presents empirical evidence gathered from diverse studies, which highlight brainwave patterns such as alpha, beta, theta, and gamma waves in relation to states of flow, focus, and creativity. Additionally, it delves into the practical implications of these findings, suggesting that athletes, musicians, and other high performers may benefit from tailored neurofeedback strategies to elevate their performance. The paper concludes by advocating for further research into how these neurophysiological markers can be utilized in coaching, therapy, and skill development, ultimately paving the way for achieving peak performance through informed interventions.

Key Words: qEEG, Brainwave Frequencies, Neurofeedback, Neuro-Physiological Signatures and Peak Performance

"*The real secret of world-class performers is not the daily routines that they develop, but that they stick to them. That they show up, even when they don't feel like it. Call it drive, call it passion, or call it grit; whatever you call it, it must come from deep within.*"

…… Brad Stulberg

Prelude

Peak decision performance is the ability to consistently reach full potential and achieve exceptional results in domains such as sports, business, and the arts. It has increasingly become a Sub of neuroscientific research. This paper attempts to examine the neural mechanisms underlying peak decision performance by integrating findings from electrophysiology, neuroimaging, and cognitive neuroscience. Key findings reveal that peak business performers are able to optimize decision performance with minimal cognitive effort, as they exhibit heightened neural efficiency, cognitive adaptability, motivation, and emotional regulation.

Understanding the neural basis of exceptional performance has long intrigued researchers. QEEG provides a window into the brain's electrical activity, enabling the identification of patterns associated with superior cognitive and motor functions. This paper aims to consolidate findings from recent studies to delineate the QEEG characteristics of peak performers. Quantitative electroencephalography (qEEG) studies support the Neural Efficiency Hypothesis, showing that high business performer's exhibit enhanced alpha wave synchronization, specifically in sensorimotor and parietal regions. This activity is associated with deep focus, reduced cognitive interference, and flow states—periods of optimal engagement and effortless execution. Furthermore, gamma wave activity has been associated with complex problem-solving and creativity, particularly in musicians and artists.

High motivation and reward sensitivity are maintained by the dopaminergic system, particularly in the striatum, according to research using functional magnetic resonance imaging (fMRI). These neural mechanisms help peak business performers sustain focus and persistence under demanding conditions. High achievers exhibit enhanced connectivity between the dorsolateral prefrontal cortex (dlPFC) and the Default Mode Network (DMN), often associated with introspective thinking. This allows for seamless transitions between strategic planning and real-time execution. Cognitive flexibility is improved by this dynamic connectivity, which is an essential quality for decision-making in fast-paced environments.

Memory and decision-making processes are also integral to peak decision performance. The hippocampus and PFC support long-term learning, executive function, and adaptability. Studies suggest that individuals with more extensive neural connections may possess stronger cognitive capabilities. Furthermore, sustained cognitive endurance has been linked to the anterior cingulate cortex's (ACC) efficiency in glucose metabolism, allowing top business performers to perform at high levels with minimal fatigue. Emotional regulation is a critical factor in peak decision performance, with confidence and motivation correlated to enhanced behavioral outcomes. Research in sports and cognitive decision performance demonstrates that individuals who can effectively regulate emotions under pressure tend to excel in high-stakes situations. This ability to regulate stress and maintain psychological resilience is an important characteristic of peak business performers.

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Beyond understanding these neural signatures, emerging interventions use neurofeedback training and non-invasive brain stimulation to improve peak decision performance. Transcranial Magnetic Stimulation (TMS), targeting the dlPFC, has shown success in enhancing decision-making and attentional control. Meanwhile, neurofeedback training enables individuals to self-regulate brainwave activity, improving focus, emotional stability, and creative output.

This paper describes how peak decision performance is supported by optimal neural efficiency, motivation, cognitive flexibility, and emotional resilience. Findings from qEEG, fMRI, and PET imaging provide compelling evidence of specialized brain mechanisms at play. Furthermore, advancements in brain stimulation and neurofeedback offer exciting possibilities for enhancing human potential. Future studies could investigate how these neuroscientific discoveries can be leveraged for decision performance optimization, bridging the gap between brain function and superior decision performance in the real world.

Peak decision performance refers to the highest level of human potential in fields like sports, business, and the arts. Understanding the neural underpinnings of peak decision performance has become an area of increasing interest in neuroscience, with the potential to inform fields as diverse as sports science, business leadership, and the arts. By leveraging neuroimaging technologies such as qEEG, fMRI, positron emission tomography (PET), and advanced neurofeedback techniques, researchers are beginning to elucidate the specific brain mechanisms that enable peak business performers to excel. This review synthesizes key findings from these methods, providing a detailed examination of the brain states associated with exceptional decision performance.

Research using qEEGs has been pivotal in exploring the electrophysiological signatures of peak decision performance. According to the Neural Efficiency Hypothesis, expert business performers exhibit heightened neural efficiency, meaning they can utilize fewer cortical resources when executing complex tasks (Kleim et al., 2004). This efficiency is especially evident in the form of increased alpha wave synchronization (8–12 Hz), particularly during self-paced activities. Alpha waves play a crucial role in relaxation and focused attention, enabling individuals to maintain flow states with minimal cognitive effort (Babiloni et al., 2009). This heightened alpha activity reflects a neural signature associated with flow states, where individuals experience effortless concentration and reduced self-awareness during demanding tasks. This supports the idea that peak business performers maintain heightened attention control while expending minimal neural effort.

Further research into alpha wave activity and flow states, characterized by complete immersion in the task, reveals that elite athletes experience increased alpha synchronization in sensorimotor regions during flow. Kao, Huang and Hung (2013) demonstrated that athletes in flow states exhibited increased alpha wave synchronization, particularly in the occipital and parietal lobes, indicating a strong relationship between alpha activity and focused task engagement. This suggests that alpha wave patterns are closely tied to the effortless attention and immersion characteristic of flow states (Babiloni et al., 2009). The connection between alpha power and flow states offers insight into how business performers achieve high levels of engagement.

Gamma wave activity (30–100 Hz) has also been linked to processes associated with creativity and problem-solving. Research by Fink and Neubauer (2006) found that individuals with high levels of creativity, such as musicians and artists, exhibit enhanced gamma wave activity in the PFC, a region associated with executive functions and cognitive control. This increased gamma activity is believed to facilitate the integration of complex information and support higher-order cognitive processes required for creative thinking found in peak business performers.

Research using fMRI scans provide high-resolution spatial data on brain activity, giving insight on the connectivity patterns that underpin peak decision performance. A key finding from fMRI research is the dopaminergic system's function in regulating motivation and reward processing during high-decision performance states. Studies found that peak business performers exhibit enhanced activation in the striatum, a region of the brain involved in reward processing and motivation (Plichta et al., 2013). This heightened activation suggests that dopaminergic pathways are more finely tuned in these individuals, allowing them to maintain focus and motivation during high-demand tasks. Motivation has also been found to improve behavioral decision performance by fine-tuning attentional processes (Engelmann et al., 2009). This aligns with evidence that dopaminergic activity plays a critical role in modulating both reward sensitivity and task engagement.

Peak decision performance has also been linked to the DMN, which is typically associated with reflective and introspective thought processes. Vatansever et al. (2017) found that high-performing individuals demonstrate increased functional connectivity between the dlPFC and the DMN, suggesting an enhanced ability to transition between introspective thinking and task-focused action. This stronger connectivity helps peak business performers' shift fluidly between reflective planning and real-time decision-making, supporting their adaptability and cognitive flexibility. This functional coupling between the dlPFC and DMN is crucial for maintaining both long-term strategic thinking and immediate focus under pressure, which is often observed in high-level cognitive tasks. Further understanding adaptibility using a neural plasticity model of intelligence suggests that intelligence develops through neural connections as a response to environmental cues (Garlick, 2002). This adaptability allows peak business performers to enhance their skills over time through training and experience.

The hippocampus and PFC are also relevant brain areas in memory and decision-making, which play crucial roles in peak decision performance. The hippocampus is integral to long-term learning and recall, while the PFC orchestrates executive function, problem-solving, and adaptive decision-making (Miller & Cohen, 2001). A study on Einstein's brain structure found that his corpus callosum was thicker than average, suggesting more extensive neural connections between hemispheres, potentially contributing to his intellectual capabilities (Men et al., 2014).

Pleasurable engagement with a task enhances decision performance by reinforcing effort and repetition. A study by Cooper et al. (2021) showed that perceived peak decision performance in strength and conditioning is associated with high-intensity positive emotions such as confidence and motivation. Moreover, a systematic review found a positive correlation between emotion regulation strategies and enhanced sports decision performance across various disciplines (Wagstaff, 2014). These findings suggest that managing emotions effectively under pressure is a crucial aspect of peak decision performance.

Additionally, glucose metabolism plays a pivotal role in cognitive decision performance. A study using PET scans demonstrated that individuals with higher cognitive decision performance on various tasks exhibited more efficient glucose metabolism in the anterior cingulate cortex (ACC), a region associated with attentional control and error detection (Volkow et al., 1997). This efficient glucose utilization is hypothesized to enable peak business performers to maintain high levels of cognitive function without experiencing the fatigue that typically affects non-experts.

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Beyond identifying neural markers of peak decision performance, researchers have investigated non-invasive techniques such as TMS and neurofeedback to enhance these neural states. Repetitive TMS applied to the dlPFC improved cognitive tasks related to decision-making and error correction, implying that TMS may be a tool for optimizing cognitive processes critical for peak decision performance (Luber & Lisanby, 2014).

Similarly, neurofeedback has shown potential to enhance decision performance across various domains. In a meta-analysis, Gruzelier (2014) demonstrated that alpha-theta neurofeedback significantly improved cognitive and creative decision performance in professional musicians and athletes. By training the brain to reach optimal states, neurofeedback enhances attention, emotional regulation, and task-specific productivity, facilitating the sustained decision performance required in high-stakes environments.

Studies on the neural correlates of peak decision performance show that a combination of optimal neuro-chemical profiles, efficient brainwave activity, and functional connectivity are linked to high achievement. The dopaminergic system and the connection between the DMN and prefrontal cortex are crucial for maintaining motivation and cognitive control, according to fMRI research, while qEEG results show that alpha and gamma wave activity is essential for reaching flow states and improving creative output. PET studies also imply that peak business performers' adaptability is supported by effective glucose metabolism in areas like the anterior cingulate cortex. Finally, emerging techniques such as (TMS) and neurofeedback present opportunities for improving brain function and greatest potential decision performance.

Introduction

Peak performance refers to the highest level of human potential in fields like sports, business, and the arts. Understanding the neural underpinnings of peak performance has become an area of increasing interest in neuroscience, with the potential to inform fields as diverse as sports science, business leadership, and the arts. By leveraging neuroimaging technologies such as quantitative electroencephalography (qEEG), functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and advanced neurofeedback techniques, researchers are beginning to elucidate the specific brain mechanisms that enable peak performers to excel. This review synthesizes key findings from these methods, providing a detailed examination of the brain states associated with exceptional performance.

Quantitative electroencephalography (qEEG) has been pivotal in exploring the electrophysiological signatures of peak performance. According to the Neural Efficiency Hypothesis, expert performers' exhibit heightened neural efficiency, meaning they can utilize fewer cortical resources when executing complex tasks (Kleim et al., 2004). This efficiency is especially evident in the form of increased alpha wave synchronization (8–12 Hz), particularly during self-paced activities. For instance, Babiloni et al. (2011) found that elite athletes exhibited increased alpha wave activity in the occipital and parietal regions, suggesting a relaxed yet focused state of mind that allows for optimal performance under pressure. This heightened alpha activity reflects a neural signature associated with flow states, where individuals experience effortless concentration and reduced self-awareness during demanding tasks. This supports the idea that peak performers maintain heightened attentional control while expending minimal neural effort.

Further research into alpha wave activity and flow states, characterized by complete immersion in the task, reveals that elite athletes experience increased alpha synchronization in sensorimotor regions during flow. Kao et al. (2013) demonstrated that athletes in flow states exhibited increased alpha wave synchronization, particularly in the occipital and parietal lobes, indicating a strong relationship between alpha activity and focused task engagement. This suggests that alpha wave patterns are closely tied to the effortless attention and immersion characteristic of flow states (Babiloni et al., 2011). The connection between alpha power and flow states offers insight into how performers achieve high levels of engagement.

Gamma wave activity (30–100 Hz) has also been linked to processes associated with creativity and problem-solving. Research by Fink and Neubauer (2006) found that individuals with high levels of creativity, such as musicians and artists, exhibit enhanced gamma wave activity in the prefrontal cortex, a region associated with executive functions and cognitive control. This increased gamma activity is believed to facilitate the integration of complex information and support higher-order cognitive processes required for creative thinking found in peak performers.

Functional Magnetic Resonance Imaging (fMRI) provides high-resolution spatial data on brain activity, giving insight on the connectivity patterns that underpin peak performance. A key finding from fMRI research is the dopaminergic system's function in regulating motivation and reward processing during high-performance states. Studies by Plichta et al. (2013) found that peak performers exhibit enhanced activation in the striatum, a region of the brain involved in reward processing and motivation. This heightened activation suggests that dopaminergic pathways are more finely tuned in these individuals, allowing them to maintain focus and motivation during high-demand tasks. This aligns with evidence that dopaminergic activity plays a critical role in modulating both reward sensitivity and task engagement.

Peak performance has also been linked to the Default Mode Network (DMN), which is typically associated with reflective and introspective thought processes. Vatansever et al. (2017) found that high-performing individuals demonstrate increased functional connectivity between the dorsolateral prefrontal cortex (dlPFC) and the default mode network (DMN), suggesting an enhanced ability to transition between introspective thinking and task-focused action. This stronger connectivity helps peak performers shift fluidly between reflective planning and real-time decision-making, supporting their adaptability and cognitive flexibility. This functional coupling between the dlPFC and DMN is crucial for maintaining both long-term strategic thinking and immediate focus under pressure, which is often observed in high-level cognitive tasks.

Single photon emission computed tomography (SPECT) and positron emission tomography (PET) provide critical insights into the neuro-chemical processes underlying peak performance. Dopamine, a key neurotransmitter involved in reward, motivation, and cognitive control, has been strongly linked to high-level performance. For instance, research by Laakso et al. (2002) using PET scans showed that elite athletes exhibited higher dopamine receptor availability in the striatum compared to non-athletes, suggesting that a more responsive dopaminergic system enhances sustained motivation and effort required for long-term peak performance.

Additionally, glucose metabolism plays a pivotal role in cognitive performance. A study by Volkow et al. (1997) using PET scans demonstrated that individuals with higher cognitive performance on various tasks exhibited more efficient glucose metabolism in the Anterior Cingulate Cortex (ACC), a region associated with attentional control and error detection. This efficient glucose utilization is hypothesized to enable peak performers to maintain high levels of cognitive function without experiencing the fatigue that typically affects non-experts.

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Understanding peak performance requires piecing together the intricate electrical rhythms of the brain and identifying the patterns that distinguish exceptional individuals from typical functioning. This exploration spans a range of high-performance domains, including elite athleticism, creative innovation, emotional resilience, and strategic leadership. Studies across high-functioning populations, such as dancers (Fink et al., 2009), musicians (Tom et al., 2016), elite marksmen (Cheng et al., 2023), and transformational leaders (Balthazard et al., 2012) have revealed consistent Electroencephalograph (EEG) traits. EEG traits include frontal alpha modulation, sensorimotor rhythm regulation, and inter-regional coherence, all of which may serve as foundational markers of peak performance. These patterns are evident during tasks and can be observed during resting states, reinforcing that peak performance may be a product of enduring neuro - physiological configurations rather than transient mental states. Recent advances in quantitative electroencephalography (QEEG) have provided a non-invasive and temporally precise method to uncover the neuro - physiological underpinnings of peak performers. These tools offer insight into how individuals regulate attention, integrate sensory input, and adaptively respond to changing demands by capturing oscillatory patterns across diverse cognitive and emotional states (Raufi & Longo, 2022; Hasan et al., 2023; Quaedflieg, 2016). By examining key markers like alpha and theta power, frontal asymmetry, coherence, and sensorimotor rhythms, researchers have begun to decode the stable traits and adaptive strategies that differentiate elite individuals from the general population and identify the patterns that distinguish exceptional individuals from typical functioning.

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Default mode network activation and Transcendental Meditation practice	Frederick Travis PhD Niyazi Parim MA- 2016- 10.1016/j.bandc.2016.08.009	Sub - 1, Sub - 4, Sub - 5, Sub - 10, Sub - 11, Sub - 12
From alpha to gamma: Electrophysiological correlates of meditation-related states of consciousness	Juergen Fell *, Nikolai Axmacher, Sven Haupt- 2010- 10.1016/j.mehy.2010.02.025	Sub - 1, Sub - 4, Sub - 5, Sub - 10
Functional neuroanatomy of meditation	Fox et al., 2010	Sub - 1, Sub - 4, Sub - 5, Sub - 10
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The Effects of Yoga Nidra Practice on EEG Oscillations	Kachera et al., 2025	Sub - 1, Sub - 10
Well-being and affective style: neural substrates and bio-behavioural correlates	Richard. J. Davidson	Sub - 1, Sub - 4, Sub - 10
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Impact of short- and long-term mindfulness meditation training on amygdala reactivity to emotional	Kral et al., 2018- 10.1016/j.neuroimage.2018.07.013	Sub - 1, Sub - 4, Sub - 5
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Scope

''Apply the components of perfect practice each time you set out to do meaningful work: •Define a purpose and concrete objectives for each working session. •Ask yourself: What do I want to learn or get done? •Focus and concentrate deeply, even if doing so isn't always enjoyable. •Single-task: The next time you feel like multitasking, remind yourself that research shows it's not effective. Keep in mind Dr. Bob's secret: "Do only one thing at a time." •Remember that quality trumps quantity."

….. Brad Stulberg

The paper begins with an overview of peak performance, defining it as the state where individuals exhibit optimal functioning across various activities. It notes crucial role of the brain in this phenomenon and introduces the use of qEEG as a means to analyze brain activity related to performance. This paper provides a detailed explanation of quantitative electroencephalography (qEEG), the technology employed in the study. It describes how qEEG differs from traditional EEG and highlights its ability to quantify brain wave patterns and identify specific neurophysiological signatures linked to different states of mind and performance levels. The paper discusses various brain wave patterns—alpha, beta, theta, and gamma—and their associations with different performance states. It illustrates how these patterns manifest during periods of heightened focus, creativity, and emotional regulation, presenting data from various studies supporting these claims. Authors explore the practical applications of the identified neurophysiological signatures. They suggest using neurofeedback to enhance performance by training individuals to modify their brainwave patterns toward those typically observed in peak performers. The paper concludes with a call for more research into the neurophysiological markers of peak performance, advocating for their use in sports psychology, educational contexts, and therapy. It encourages interdisciplinary collaboration to refine training methodologies and interventions based on qEEG findings.

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Gaps in Literature

While the current body of QEEG research provides valuable insights into the neural correlates of peak performance, several limitations persist. Although some studies have shown that stress impairs attentional processes, recent work (Yan et al., 2024) suggests that acute stress may also enhance inhibitory control through increases in frontal theta and beta activity. This contradictory evidence highlights the need for further research to explore the boundary conditions under which stress supports or hinders peak performance. Furthermore, many studies suffer from small sample sizes, lack of replication, or limited generalizability beyond specific performance domains. For example, most leadership studies focus narrowly on transformational traits without accounting for cultural context or alternative leadership models. There is also a lack of longitudinal evidence to determine whether the identified EEG markers are stable traits or modifiable through training. Further, findings from microstate research and parietal theta modulation are often inconclusive or trend-level, underscoring the need for multimodal and more granular measurement tools. Integrating behavioral, hormonal, and cognitive metrics with QEEG will help create a more comprehensive understanding of peak functioning.

How can the principles of emotional intelligence be applied to team settings for achieving peak performance? In what ways does a growth mindset influence a person's approach to setbacks and failures? What is the significance of feedback mechanisms in the pursuit of peak performance? How does the concept of flow relate to achieving peak performance in high-pressure situations? While QEEG research has illuminated valuable neural traits linked to peak performance, several avenues remain underexplored and warrant deeper empirical attention. For instance, machine learning approaches have proven effective in classifying dominant leadership traits from resting-state EEG (Nakuci et al., 2023), yet their application remains limited to leadership contexts. Expanding such models to populations like athletes, artists, and high-performing students would help establish whether universal QEEG signatures of adaptability exist across high-functioning groups or whether neural efficiency is domain-specific.

Additionally, findings from Chenot et al. (2024) and Keunho Yoo et al. (2024) highlight inconsistencies in the predictive value of EEG microstates and spectral power in resilience contexts. While these studies offer important insights, their limited statistical power and reliance on narrow behavioral correlates underscore the need for replication with larger, more diverse cohorts. The integration of EEG with behavioral measures, hormonal assays, and real-time performance monitoring could yield a more multidimensional understanding of adaptability.

The emphasis on transformational leadership in current EEG literature, most notably by Balthazard et al. (2012) and Edison et al. (2019), has led to a narrow characterization of effective leadership styles. Future studies should include alternative frameworks, such as servant leadership, distributed leadership, or culturally nuanced models, to better reflect the diversity of high-performance leadership in real-world settings.

Finally, emerging evidence from neurofeedback studies and portable EEG platforms points toward the feasibility of individualized cognitive training. Rather than simply classifying peak performers post hoc, future research should explore how QEEG markers can guide real-time, adaptive interventions. The transition from diagnostic to developmental use of EEG holds promise for education, executive coaching, and clinical training. By addressing these gaps across populations, paradigms, and methodological approaches, future studies can move the field closer to a robust, generalizable framework for understanding and enhancing peak performance through neuro-electric science. Understanding peak performance requires piecing together intricate electrical rhythms of brain and identifying patterns that distinguish exceptional individuals from typical functioning. Paper aims to comprehend quantitative electroencephalography (QEEG) to uncover neurophysiological underpinnings of peak performers. Paper adopts EEG traits include frontal alpha modulation, sensorimotor rhythm regulation, and inter-regional coherence that serve as foundational markers of peak performance. These patterns are observed during resting states, reinforcing that peak performance is product of enduring neurophysiological configurations rather than transient mental states. Paper explores how individuals regulate attention, integrate sensory input and adaptively respond to changing demands by capturing oscillatory patterns across diverse cognitive and emotional states. Examining alpha and theta power, frontal asymmetry, coherence and sensorimotor rhythms, paper attempts through Resilience Recovery Time, elevated alpha power under resting conditions, refined sensorimotor rhythms, efficient alpha/theta ratios and asymmetrical frontal engagement to decode stable traits and adaptive strategies that differentiate individuals that distinguish exceptional individuals from typical functioning. Findings suggest elevated alpha reflect ability to sustain focused yet flexible mental states, crucial for innovation and performance under complexity. Neurofeedback enabled conscious control over these patterns, reinforcing hypothesis that ability to modulate one's brain state is critical to sustained performance. Paper offers future directions in deciphering predictive value of EEG microstates and spectral power in resilience contexts. Paper points at future research in exploring how QEEG markers can guide real-time, adaptive interventions for understanding and enhancing peak performance.

Peak performance is not defined by a single ratio, band, or condition, but by the recurring, flexible orchestration of QEEG patterns. Whether under pressure, during creative ideation, or in quiet leadership reflection, high performers display synchronized neuro-electric rhythms that balance stability with adaptability. Across diverse domains, ranging from leadership and creative ideation to elite athleticism and stress adaptation, high performers exhibit stable yet dynamic neural configurations. These include elevated alpha power under resting conditions (Fink et al., 2009; Tom et al., 2016), refined sensorimotor rhythms (Cheng et al., 2023), efficient alpha/theta ratios (Raufi & Longo, 2022), and asymmetrical frontal engagement in emotionally or cognitively taxing contexts (Quaedflieg, 2016; Konvalinka et al., 2014).

Critically, these features do not function in isolation. Rather, they appear to reflect underlying neural efficiency, attentional control, and adaptive flexibility, traits observable not only through task-related performance but also at rest (Balthazard et al., 2012; Edison et al., 2019). Research using ERP components (e.g., N170; Gu et al., 2023) and phase-locking duration (PLD; Balthazard et al., 2012) further highlights the temporal coordination required for high-level functioning.

The converging literature suggests that peak performers possess an intrinsic readiness, shaped by their ability to down regulate irrelevant activity, synchronize relevant cortical regions, and recover rapidly from stressors. While the evidence remains strongest in domains like transformational leadership and sports, similar principles likely apply across high-demand environments. As Dimitriadis et al. (2023) and Keunho Yoo et al. (2024) emphasize, even small delays in neural recovery, such as prolonged beta activity after stress, may serve as subtle indicators of reduced resilience or inefficiency.

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In this light, QEEG does not merely document differences in performance. It provides a dynamic blueprint of the cognitive and emotional regulation systems' real-time operation. As the field matures, leveraging these patterns through neurofeedback or adaptive training could become central to enhancing human performance across professions. The synthesis of electrophysiological evidence thus lays the groundwork for a coherent, evidence-based model of neuro--cognitive excellence. Whether under pressure, during creative ideation, or in quiet leadership reflection, high performers display synchronized neuro-electric rhythms that balance stability with adaptability. This view is further reinforced by findings from Yan et al. (2024), who observed that acute stress can enhance inhibitory control, marked by increased frontal theta and beta activity, demonstrating that high performers may leverage stress to sharpen cognitive control rather than succumb to it.

Theoretical Framework

Understanding the neural basis of exceptional performance has long intrigued researchers. QEEG provides a window into the brain's electrical activity, enabling the identification of patterns associated with superior cognitive and motor functions. This paper aims to consolidate findings from recent studies to delineate the QEEG characteristics of peak performers. Peak performance in various domains—ranging from leadership and executive functions to athletics and creative endeavors—is often underpinned by distinct neuro - physiological patterns. Quantitative Electroencephalography (QEEG) has emerged as a pivotal tool in identifying these patterns, offering insights into the neural correlates of elite performance. This paper synthesizes current literature on QEEG findings related to peak performers, highlighting consistent markers such as frontal midline theta activity, gamma oscillations, and theta/beta ratios. The implications of these findings for performance enhancement and neurofeedback interventions are also discussed.

Sensorimotor Rhythm (SMR) Enhancement

Elevated SMR activity, typically in the 12–15 Hz range, has been consistently observed in elite performers. For instance, a study on skilled marksmen revealed that those with superior shooting accuracy exhibited higher SMR levels prior to trigger pull, suggesting a state of optimal motor readiness and reduced extraneous movement.

Frontal Midline Theta Activity

Frontal midline theta (Fm theta) activity, associated with focused attention and cognitive control, is another hallmark of peak performance. In tasks requiring sustained attention and decision-making, increased Fm theta has been linked to better outcomes.

Frontal Midline Theta Activity and Executive Function

Frontal midline theta (Fm theta) activity, typically observed in the 4–7 Hz range, is associated with focused attention and cognitive control. In tasks requiring sustained attention and decision-making, increased Fm theta has been linked to better outcomes. For instance, studies have demonstrated that higher frontal theta activity during cognitive tasks predicts better performance, while higher resting-state theta power is associated with lower cognitive functioning

Gamma Oscillations and Cognitive Integration

Gamma oscillations (>30 Hz) are implicated in higher-order cognitive processes, including perception, memory, and consciousness. Research indicates that increased gamma activity, particularly in the frontal regions, correlates with enhanced cognitive performance. For example, a study demonstrated that higher frontal theta-gamma coupling predicted better working memory performance

Theta/Beta Ratios and Attention Regulation

The theta/beta ratio (TBR) is a commonly used metric in QEEG studies to assess attentional control. A lower TBR is generally associated with improved executive function and attentional regulation. Neurofeedback training aimed at reducing TBR has been shown to enhance cognitive performance in healthy individuals.

Coherence Patterns

Coherence analyses reveal the functional connectivity between different brain regions. Studies have shown that peak performers often exhibit specific coherence patterns, such as reduced Fz-T3 coherence during optimal performance states, indicating efficient neural processing with minimal interference from non-essential regions.

In professional female soccer players, increased alpha band power and delta band coherence were associated with lower anxiety levels and enhanced decision-making capabilities, respectively. These findings underscore the role of these frequency bands in emotional regulation and cognitive processing during high-pressure situations.

Key Neural Signatures Summary

- **Alpha Frequency (8–13 Hz):** Lower posterior alpha is associated with reduced anxiety, while increased alpha represents relaxed wakefulness and high attentional control in experts.
- **Theta Frequency (4–8 Hz):** Increased frontal theta is associated with high cognitive control, immersion, and concentration in the "flow" state.
- **Delta Frequency (1–4 Hz):** High coherence in delta band is linked to good decision-making and affective responses to environmental stimuli.
- **SMR (Sensorimotor Rhythm, 12–15 Hz):** Higher SMR is associated with reduced muscle movement and increased focus in shooting/precision tasks.
- **Theta/Beta Ratio (TBR):** Decreased TBR indicates better attentional control.

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Practical Proposition

Mapping Neuro-Electric Patterns in Peak Performance

Understanding peak performance requires piecing together the intricate electrical rhythms of the brain and identifying the patterns that distinguish exceptional individuals from typical functioning. This exploration spans a range of high-performance domains, including elite athleticism, creative innovation, emotional resilience, and strategic leadership. Studies across high-functioning populations, such as dancers (Fink et al., 2009), musicians (Tom et al., 2016), elite marksmen (Cheng et al., 2023), and transformational leaders (Balthazard et al., 2012) have revealed consistent Electroencephalograph (EEG) traits. EEG traits include frontal alpha modulation, sensorimotor rhythm regulation, and inter-regional coherence, all of which may serve as foundational markers of peak performance. These patterns are evident during tasks and can be observed during resting states, reinforcing that peak performance may be a product of enduring neuro - physiological configurations rather than transient mental states. Recent advances in quantitative electroencephalography (QEEG) have provided a non-invasive and temporally precise method to uncover the neuro - physiological underpinnings of peak performers. These tools offer insight into how individuals regulate attention, integrate sensory input, and adaptively respond to changing demands by capturing oscillatory patterns across diverse cognitive and emotional states (Raufi & Longo, 2022; Hasan et al., 2023; Quaedflieg, 2016). By examining key markers like alpha and theta power, frontal asymmetry, coherence, and sensorimotor rhythms, researchers have begun to decode the stable traits and adaptive strategies that differentiate elite individuals from the general population and identify the patterns that distinguish exceptional individuals from typical functioning.

Foundations of QEEG: Frequency Bands and Mental States

QEEG draws on early electrophysiological research that identified delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (>30 Hz) canonical frequency bands. Each of these is linked to distinct mental states and functional capacities, which have been associated with sleep, internal attention, relaxation, cognitive processing, and high-order integration, respectively (Sanei & Chambers, 2007). QEEG can quantify habitual brain activity patterns of enhancement or reduction of alpha for attention and cognitive control. Enhanced frontal alpha power has been repeatedly found among individuals with high IQ and creative experts, such as dancers and musicians, which supports internally directed attention and reduces cognitive interference (Doppelmayr et al., 2002; Fink et al., 2009; Tom et al., 2016). These findings suggest that elevated alpha may reflect an ability to sustain focused yet flexible mental states, crucial for innovation and performance under complexity (Fink et al., 2009; Tom et al., 2016). Notably, alpha suppression, especially in the left frontal regions, also emerges in contexts demanding anticipation and cognitive control, such as leadership and motor readiness (Balthazard et al., 2012; Quaedflieg, 2016). Motor readiness is pivotal for athletes, who demonstrated a lower change in alpha between eyes-closed and eyes-open states (ΔEC-EO alpha) has been associated with enhanced visuospatial integration and sport-specific efficiency (Ramyarangsi et al., 2024).

The alpha/theta ratio (ATR) is also a robust marker for executive functioning and mental clarity. Raufi and Longo (2022) found that individuals with higher ATR demonstrated reduced mental workload and improved cognitive efficiency. This complements earlier work showing that deviations in ATR are common among clinical populations such as those with ADHD, where reduced coherence and atypical spectral ratios mark executive dysfunction (Cantor & Chabot, 2009; Ciftci et al., 2025). Cantor and Chabot (2009) also demonstrated that QEEG deviations, particularly increased frontal theta and reduced posterior alpha, could reliably distinguish children with ADHD from learning-disordered and typically developing groups, with discriminant accuracies exceeding 95%. These differences, consistent across age-regressed QEEG features, suggest that trait-like neural inefficiencies persist across childhood and adolescence in clinical populations, sharply contrasting with the more synchronized and efficient profiles seen in high-functioning individuals. In contrast, peak performers appear to maintain a flexible but elevated ATR profile, balancing internal processing (theta) with suppressive control (alpha).

QEEG Signatures of Cognitive Agility and Stress Resilience

Peak cognition does not rely solely on quiet alertness associated with alpha rhythms; rather, it requires the capacity to remain engaged and flexible in the face of cognitive demands, including under stress. In some cases, acute stress may enhance rather than impair cognitive performance through improved inhibitory control by increased attentional engagement (Yan et al., 2024). Through the utilization of a modified stop-signal task while recording EEG, it was found that participants under acute stress showed significantly shorter stop-signal reaction times (SSRTs), a key marker of enhanced inhibitory control. EEG data revealed increased frontal theta and beta activity during the inhibition phase, suggesting stronger top-down regulation. These findings highlight that in high-functioning individuals, stress may serve to mobilize cognitive resources and enhance attentional focus, ultimately supporting adaptive executive control.

Additionally, gamma and beta bursts become critical under challenging or novel conditions. Acute stress research shows that individuals with efficient adaptive tendencies exhibit increased beta power and transient gamma synchronization, particularly in prefrontal regions (Hasan et al., 2023; Quaedflieg, 2016). Quaedflieg's (2016) research further contextualized these responses by examining the dynamic interaction between the autonomic nervous system and the hypothalamic-pituitary-adrenal (HPA) axis under acute stress. The research's findings emphasized the role of frontal EEG alpha asymmetry as a neuro - physiological marker of resilience, particularly highlighting that individual with greater left-lateralized frontal activity exhibited lower cortisol reactivity and greater affective control during recovery. These changes reflect executive reconfiguration, a cognitive pivot point allowing for rapid prioritization and reallocation of mental resources—a hallmark of resilience and leadership.

Building on this integration of attentional regulation and stress adaptability, elite performance has also been linked to domain-specific sensorimotor efficiency. In high-precision motor tasks, such as those performed by elite marksmen, QEEG studies have shown that top performers demonstrate increased sensorimotor rhythm (SMR) activity and reduced interference from irrelevant cortical regions, which are markers of psychomotor efficiency and focus (Cheng et al., 2023). Similarly, in high-stakes decision-making contexts, such as those encountered by transformational leaders, QEEG reveals consistent patterns of greater SMR coherence, lower resting-state alpha, and balanced inter-hemispheric frontal activity (Balthazard et al., 2012; Edison et al., 2019). These spectral profiles predict leadership performance as assessed by a validated instrument called the Multifactor Leadership Questionnaire (MLQ). This instrument measures transformational, transactional, and laissez-faire leadership behaviors, predicting leadership effectiveness and follower outcomes, but also reflects behavioral adaptability and strategic flexibility. Balthazard et al. (2012) conducted one of the most detailed QEEG analyses, differentiating

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transformational from non-transformational leaders, examining coherence, amplitude asymmetry, and phase-locking duration (PLD) across cortical sites. Analysis revealed that transformational leaders exhibited significantly greater interhemispheric alpha coherence, especially in the frontal and central regions, along with reduced beta amplitude asymmetry, which are markers linked to superior emotional regulation and cognitive flexibility. PLD, which reflects the temporal stability of phase relationships between signals, was also higher among transformational leaders, suggesting more synchronized and efficient neural communication during rest. Edison et al. (2019) framed their investigation within VUCA environments, characterized by volatility, uncertainty, complexity, and ambiguity, which demand heightened cognitive and emotional adaptability. Using EEG brain mapping alongside MLQ and Wechsler assessments, they confirmed that all participants identified as transformational leaders shared similar frontal and temporal alpha/beta activity patterns in the resting state.

Additionally, neurofeedback training enabled conscious control over these patterns, reinforcing the hypothesis that the ability to modulate one's brain state is critical to sustained leadership performance. Sustained and efficient high leadership also entails neuro-cognitive processes such as cortical engagement and reduced inhibition, which involves N170, an event-related potential (ERP) component (Gu et al., 2023). They used ERP and time–frequency EEG analysis during facial emotion recognition tasks and found that high-leadership individuals displayed enhanced N170 amplitudes and greater alpha de-synchronization, indicating superior structural face encoding and emotional processing flexibility. These traits are especially relevant for leaders, as they reflect heightened sensitivity to social cues and a greater ability to regulate and interpret emotional expressions in interpersonal contexts. Executive functions such as attentional control, working memory, and goal-directed behavior involve the dorsolateral prefrontal cortex (DLPFC) and have also been studied by Balconi et al. (2023) in the context of interactive leadership. They utilized EEG hyperscanning with leader-employee dyads during performance reviews, revealing that the absence of quantitative rating (a more empathic context) led to stronger frontal delta and theta activation, higher inter-brain coherence, and increased beta activity in left DLPFC regions, which is tied to empathy, attentional control, and approach-oriented behavior. This aligns with broader findings that interpersonal emotional tuning and empathic engagement may be critical neural components of effective leadership. Together, these findings suggest that despite differences in domain, both elite athletes and transformational leaders share a neuro - physiological foundation of rapid adaptation, precision control, and context-sensitive responsiveness.

Resilience Recovery and EEG: Real-Time Adaptability in Leadership Contexts

Branching further towards future leaders, research into resilience using Stroop-induced EEG tasks has shown that MBA students with better EEG recovery curves also perform better on resilience indices (Lambert et al., 2023). EEG-based recovery from adversity, indexed through normalization of alpha and beta after stressor offset, highlights one of the most practical QEEG signatures of leadership potential. Additional empirical support has been provided by Dimitriadis et al. (2023), who implemented EEG to measure Resilience Recovery Time (RRT) in postgraduate executive MBA students undergoing an emotionally charged Stroop test. The study revealed gender-based differences in beta wave recovery patterns. Males returned to baseline within 6 seconds, while females required over 10 seconds, suggesting differential resilience capacities. The findings underscore the utility of EEG in detecting moment-to-moment neural recovery and highlight the implications of stress recovery dynamics in future leadership training and development. Further supporting this idea, Keunho Yoo et al. (2024) examined the use of resting-state EEG spectral analysis to assess psychological resilience in a healthy adult population. While no EEG frequency band reached statistical significance, P4, an electrode site located over the right parietal cortex, showed a trend-level increase in theta power. This parietal region is typically associated with attentional reorienting and self-regulation, suggesting that theta power at P4 approached significance ($p = 0.081$), suggesting parietal theta as a potential correlate of stress adaptability. The study highlights both the promise and limitations of using resting EEG as a biomarker for resilience and calls for larger sample sizes and multimodal approaches.

Resting-State Microstates and Limitations in Cognitive Prediction

Resting-state EEG microstate dynamics have been proposed as potential indicators of how the brain transitions between cognitive states. For peak performers, efficient microstate transitions may support the ability to flexibly alternate between internally focused and externally driven tasks—an attribute often described behaviorally but difficult to quantify neurologically. However, findings by Chenot et al. (2024) complicate this picture. Their study found no significant association between microstate C, typically linked to salience processing and network switching, and microstate D, associated with sustained attention and task maintenance, and composite scores of executive functioning. Despite earlier research suggesting a connection between microstate profiles and fluid intelligence, these null results highlight the need for caution in treating EEG microstates as reliable, standalone biomarkers. More comprehensive approaches using larger samples and multimodal methods are required to determine their utility in peak performance contexts.

Literature has not only established that peak performers excel under stress or focus under calm, but also their habitual readiness, as revealed in resting EEG. This is supported by findings in elite athletes, expert marksmen, and individuals with high social cognition, all of whom exhibit fine-tuned SMR, alpha coherence, and reduced frontal interference during baseline recordings (Cheng et al., 2023; Keunho Yoo et al., 2024).

Methodology

QEEG offers valuable insights into the neuro - physiological underpinnings of peak performance. Consistent patterns, including elevated frontal midline theta activity, increased gamma oscillations, and optimized theta/beta ratios, characterize elite performers across various domains. Leveraging these findings can inform targeted neurofeedback interventions and performance optimization strategies.

The identification of these QEEG markers has practical implications. Neurofeedback training protocols can be tailored to enhance specific brainwave activities, such as SMR and Fm theta, to cultivate states conducive to peak performance. Moreover, real-time QEEG assessments can serve as diagnostic tools to monitor an individual's readiness and guide interventions accordingly.

A comprehensive review of peer-reviewed articles published between 2015 and 2025 was conducted, focusing on studies that employed QEEG to assess individuals identified as peak performers in various fields. Databases such as PubMed, PMC, and SpringerLink were utilized for this purpose.

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QEEG offers valuable insights into the neuro - physiological underpinnings of peak performance. Consistent patterns, including elevated SMR, increased frontal midline theta activity, and specific coherence configurations, characterize elite performers across various domains. Leveraging these findings can inform targeted neurofeedback interventions and performance optimization strategies.

Sub: Description and Neural – Picture

Prompts: Cognitive Ascetic with Dynamic Precision

1. ‘Alpha and theta oscillations are inversely related to progressive levels of meditation depth’- Katyal & Goldin, 2021
2. ‘Default mode network activation and Transcendental Meditation practice’- Travis & Parim, 2016
3. ‘From alpha to gamma: Electrophysiological correlates of meditation-related states of consciousness’- Fell & Sven Haupt, 2010
4. ‘Functional neuroanatomy of meditation: A review and meta analysis of 78 functional neuroimaging investigations’- Fox et al., 2010
5. ‘Meditation States and Traits: EEG, ERP, and Neuroimaging Studies- Cahn & Polich, 2006
6. ‘A self-referential default brain state: patterns of coherence, power, and eLORETA sources during eyes-closed rest and Transcendental Meditation practice’- Travis et al., 2009
7. ‘Central and autonomic nervous system interaction is altered by short-term meditation’- Tang et al., 2009
8. ‘The Effects of Yoga Nidra Practice on EEG Oscillations: A Systematic Review’- Kachera et al., 2025
9. ‘Well-being and affective style: neural substrates and biobehavioural correlates’- Davidson
10. ‘ASMR amplifies low frequency and reduces high frequency oscillations ‘- Swart et al., 2021
11. ‘Data for default network reduced functional connectivity in meditators, negatively correlated with meditation expertise’- Berkovich-Ohana et el., 2016
12. ‘Effects of acute aerobic exercise or meditation on emotional regulation’- Edwards et al., 2016
13. ‘Impact of short- and long-term mindfulness meditation training on amygdala reactivity to emotional stimuli’- Kral et al., 2018
14. ‘Modulation of human frontal midline theta by neurofeedback’- Pfeiffer et al., 2024
15. ‘Neural dynamics of mindfulness meditation and hypnosis’- Bauer et al., 2022

The Strategist

1. ‘Classification of executive functioning performance post-longitudinal tDCS using functional connectivity and machine learning methods’- Rao et al., 2023
2. ‘Review of EEG Affective Recognition with a Neuroscience Perspective’ Lim et al., 2024
3. ‘EEG Signatures of Resilience Across Individuals With High and Low Anxiety’- Gupta & Reddy, 2025
4. ‘Psychological resilience correlates with EEG source-space brain network flexibility’- Paban et al., 2019
5. ‘Simultaneously exploring multi-scale and asymmetric EEG features for emotion recognition ‘- Wu et al., 2022
6. ‘EEG Study on Emotional Intelligence and Advertising Message Effectiveness’- Ciorciari et al., 2019
7. ‘EEG-neurofeedback and executive function enhancement in healthy adults: A systematic review’- Viviani & Vallesi, 2021
8. ‘Prediction of Human Empathy based on EEG Cortical Asymmetry’- Kuljit & Alimardani, 2020
9. ‘Altered neural processes underlying executive function in occupational burnout’- Pihlaja et al., 2023
10. ‘Neurophysiological dynamics for psychological resilience’- Watanabe & Takeda, 2021
11. ‘Power spectral analysis of resting-state EEG to monitor psychological resilience to stress’- KeunhoYoo et al., 2024
12. ‘Slow-wave brain connectivity predicts executive functioning and group belonging in socially vulnerable individuals’- Lanfranco et al., 2024

The Mnemonic Synthesizer

1. ‘EEG markers of successful allocentric spatial working memory maintenance in humans’- Meziane et al., 2024
2. ‘Relationship Between Alpha Rhythm and the Default Mode Network: An EEG-fMRI Study’- Bowman et al., 2017
3. ‘Visual Working Memory Recruits Two Functionally Distinct Alpha Rhythms in Posterior Cortex ‘- Rodriguez-Larios et al. 2022
4. ‘Alpha-Band Phase Synchrony Is Related to Activity in the Fronto-Parietal Adaptive Control Network’- Sadaghiani et al., 2012
5. ‘The Default Mode Network and EEG Regional Spectral Power: A Simultaneous fMRI-EEG Study’- Neuner et al., 2014
6. ‘EEG alpha oscillations: The inhibition–timing hypothesis’- Klimesch et al., 2006
7. ‘Electroencephalogram Signal Correlations between Default Mode Network and Attentional Functioning’- Matsuo et al., 2024
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Neuro-Spiritual Visionary

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2. Default mode network activation and Transcendental Meditation practice-Travis & Parim, 2016
3. From alpha to gamma: Electrophysiological correlates of meditation-related states of consciousness- Fell et al., 2010
4. 'Functional neuroanatomy of+meditation: A review and meta analysis of 78 functional neuroimaging investigations'- Fox et al., 2010
5. 'Meditation States and Traits: EEG, ERP, and Neuroimaging Studies- Cahn & Polich, 2006
6. 'A self-referential default brain state: patterns of coherence, power, and eLORETA sources during eyes-closed rest and Transcendental Meditation practice'- Travis et al., 2009
7. 'Central and autonomic nervous system interaction is altered by short-term meditation'- Tang et al., 2009
8. Well-being and affective style: neural substrates and biobehavioural correlates-Davidson
9. ASMR amplifies low frequency and reduces high frequency oscillations- Swart et al., 2021
10. Impact of short- and long-term mindfulness meditation training on amygdala reactivity to emotional stimuli- Kral et al., 2018
11. Modulation of human frontal midline theta by neurofeedback- Pfeiffer et al., 2024
12. Neural dynamics of mindfulness meditation and hypnosis- Bauer et al., 2022
13. Effect of Bhramari Pranayama on response inhibition: Evidence from the stop signal task- Rajesh et al., 2014
14. Functional connectivity and power spectral density analysis of EEG signals in trained practitioners of Bhramari pranayama- Malan et al., 2023
15. Hemisphere-specific EEG related to alternate nostril yoga breathing- Telles et al., 2017
16. EEG theta/beta ratio as a potential biomarker for attentional control and resilience against deleterious effects of stress on attention- Putman et al., 2014
17. Sleep Quality and Electroencephalogram Delta Power- Long et al., 2021
18. EEG-Based Assessment of Cognitive Resilience via Interpretable Machine Learning Models- Kakkos et al., 2025

Mystical Resonator

1. Alpha and theta oscillations are inversely related to progressive levels of meditation depth- Katya & Goldin, 2021
2. Default mode network activation and Transcendental Meditation practice- Travis & Parim, 2016
3. From alpha to gamma: Electrophysiological correlates of meditation- related states of consciousness- Fell et al., 2010
4. 'Functional neuroanatomy of+meditation: A review and meta analysis of 78 functional neuroimaging investigations'- Fox et al., 2010
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3. EEG-Based Assessment of Cognitive Resilience via Interpretable Machine Learning Models- Kakkos et al., 2025
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6. Asymmetrical Electroencephalographic Change of Human Brain During Sleep Onset Period- Park & Shin, 2017
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12. EEG Correlates of Cognitive Dynamics in Task Resumption after Interruptions: The Impact of Available Time and Flexibility- Ulku et al., 2025
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Visionary Executor

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3. Power spectral analysis of resting-state EEG to monitor psychological resilience to stress- Keunho Yoo et al., 2024
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6. Electroencephalographic (EEG) Brain Wave Patterns as Descriptors of Financial Risk-Taking Behavior- Kwak & Grable, 2025
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10. Identifying neurophysiological correlates of stress- Pei et al., 2024
11. Theta activity and cognitive functioning: Integrating evidence from resting-state and task-related developmental electroencephalography (EEG) research- Tan et al., 2024
12. Relationship Between Alpha Rhythm and the Default Mode Network: An EEG-fMRI Study- Bowman et al., 2017

Resonant Polymath

1. Analysis of frequency dependent Vedic chanting and its influence on neural activity of humans- Nalluri et al., 2023
2. Delta Wave Power: An Independent Sleep Phenotype or Epiphenomenon? – Davis et al., 2025
3. Anything but small: Microarousals stand at the crossroad between nor adrenaline signaling and key sleep functions- Luthi & Nedergaard, 2025
4. From macro to micro: slow-wave sleep and its pivotal health implications- Ishii et al., 2024
5. The Role of Emotion Regulation and Awareness in Psychosocial Stress: An EEG-Psychometric Correlational Study – Allegretta et al., 2024
6. Visual-spatial sequence learning and memory in trained musicians- Anaya et al., 2017
7. Art and brain: insights from neuropsychology, biology and evolution- Zaidel
8. Effects of Drawing on Alpha Activity: A Quantitative EEG Study With Implications for Art Therapy – Belkofer et al., 2014
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19. EEG theta/beta ratio as a potential biomarker for attentional control and resilience against deleterious effects of stres on attention – Putman et al., 2014
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21. EEG-Based Assessment of Cognitive Resilience via Interpretable Machine Learning Models- Kakkos et al., 2025
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14. Well-being and affective style: neural substrates and biobehavioural correlates – Davidson
15. Study of immediate neurological and autonomic changes during kapalbhati pranayama in yoga practitioners- Malhotra et al., 2022
16. Effect of Bhramari Pranayama on response inhibition: Evidence from the stop signal task – Malhotra et al., 2022
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Strategic Visionary

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2. EEG theta/beta ratio as a potential biomarker for attentional control and resilience against deleterious effects of stress on attention – Putman et al., 2014
3. Sleep Quality and Electroencephalogram Delta Power- Long et al., 2021
4. EEG measures index neural and cognitive recovery from sleep- Mander et al., 2010
5. Delta Wave Power: An Independent Sleep Phenotype or Epiphenomenon? Davis et al., 2025
6. Anything but small: Microarousals stand at the crossroad between noradrenaline signaling and key sleep functions- Luthi & Nedergaard, 2025
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Mystical Integrator

1. Default mode network activation and Transcendental Meditation practice – Travis & Parim, 2016
2. EEG theta/beta ratio as a potential biomarker for attentional control and resilience against deleterious effects of stress on attention – Putman et al., 2014
3. Sleep Quality and Electroencephalogram Delta Power- Long et al., 2021
4. EEG-Based Assessment of Cognitive Resilience via Interpretable Machine Learning Models- Kakkos et al., 2025
5. EEG measures index neural and cognitive recovery from sleep- Mander et al., 2010
6. Anything but small: Microarousals stand at the crossroad between nor adrenaline signaling and key sleep functions- Luthi & Nedergaard, 2025
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13. Revealing brain's cognitive process deeply: a study of the consistent EEG patterns of audio-visual perceptual holistic - Li et al., 2024

Internal Integrator

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2. Functional connectivity and power spectral density analysis of EEG signals in trained practitioners of Bhramari pranayama- Malan et al., 2023
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17. Yoga and Brain Wave Coherence: A Systematic Review for Brain Function Improvement – De & Mondal, 2020

1. **Sub – 1**: Cognitive Ascetic with Dynamic Precision

A neural archetype marked by meditative mastery, emotional composure, and highly efficient task engagement—capable of transitioning between deep introspective calm and high-demand executive processing.

- He was a monk for most of his life.
- Now a businessman and successful as well (monetarily also).
- Gamma activity may be contributing to his 'other realm experience', and low theta/beta ratios to his calm composure.
- Need to find a link between his established neural signature to his current career growth.

2. **Sub – 2**: The Strategist

A high-level executive neural profile characterized by strong **executive control (Fz),** excellent **alpha modulation, relaxation**, and lower **HiBeta in EO. This could** suggest strategic drive and readiness, not pathology.

- Heads the office for the Ambanis
- Look for the markers that aid in enhanced executive function.
- Markers that show a burnout could be balanced out by other markers.
- His ability to retain such an important position over a long period speaks volumes of his character, ethics, morality, and resilience.

3. **Sub - 3**- The Mnemonic Synthesizer

This individual's brain demonstrates an exceptional capacity to toggle between deep internal rest and intense multi-threaded cognitive activation**.** They access vast stores of information while maintaining physiological calm, likely relying on gamma-indexed memory networks and alpha-driven suppression of irrelevant stimuli**.** Neural signatures are aligned with high-control performers**,** creative logic savants**,** or autodidacts**.**

- Ability to remember 100 questions posed at the same time by different people and answer them accurately.

4. **Sub - 4**- The Neuro-Spiritual Visionary

This individual embodies the archetype of a **Neuro-Spiritual Visionary** — a rare integration of scientific precision, emotional intelligence, and spiritual insight. Her brain shows clear evidence of **disciplined cognitive control**, **meditative mastery**, and **transcendence of past trauma**.

- Strong academic background.
- Significant emotional trauma about 10 years ago (roughly)
- Chose to heal through meditation
- Drive to make the world a better place as she is a 'brain plumber'
- Always on the move to do make a significant impact

5. **Sub - 5**- The Mystical Resonator

This profile aligns with the **"Mystical Resonator" archetype** — a rare neural configuration combining **trance-absorption, flow-state modulation, sensory-motor empathy, expanded awareness, and voice-somatic integration.**

- Ability to swirl continuously for 8 hours
- Talented with the use of Sufi musical instruments for healing
- Also sings very well

6. **Sub - 6**- The Strategic Integrator

This advisor's (to a Sheikh in the UAE) neural signature matches the Strategic Integrator archetype. An individual whose brain prioritizes depth over speed**,** foresight over reaction, and symbolic abstraction over routine vigilance.

- They maintain **high frontal regulation, selective posterior synchronization**, and **gamma-bound visual cognition** — ideal for **advisory roles, big-picture planning**, and **nonlinear problem-solving** under pressure.

- Deviations from some peak markers are not deficiencies — they could be recalibrations that reflect **role-based optimization.**

7. **Sub - 7**- The Visionary Executor

This neural profile belongs to individual who: Sees future while course-plotting present. Balances vision and execution with laser-like decisiveness. His brain is wired for high-risk tolerance, resilience, cognitive adaptability**,** and strategic dominance

- Started life in Dubai carrying AED 1000.
- Worked his way up and now his business earns him AED 50k per hour
- 2000 employees under him

8. **Sub - 8**- The Resonant Polymath

This archetype represents the rare convergence of verbal, visual, and emotional intelligences. The Resonant Polymath navigates complexity with rhythmic clarity, using internalized linguistic patterns (e.g., Sanskrit chanting) to regulate emotional arousal and cognitive fluidity. Her EEG signature reflects neuro-cognitive versatility: high-frequency alpha for executive oversight, dynamic gamma reactivity for integrative problem solving, and adaptive deviations that reflect a life built on creative vision, relational presence, and academic integrity**.** She thrives not by quieting the mind, but by synchronizing it — across roles, rhythms, and responsibilities.

- Trained in Carnatic classical music and recital of Sanskrit shlokas in pre-adolescence (7 years onwards). Continues to chant many Sanskrit shlokas twice a day and has learned all of them in the process.
- Pursued sketching (starting at 5 years), progressed to rendering with charcoal with correct use of light and shadows (10 years till present)
- Enrolled in architecture by securing a 2-digit state rank in the common exam for this course, scholarship student. Family responsibilities at a very early age did not permit her to practice post-graduation.
- Started painting at the age of 33, created a series of ballerinas with her signature 3d flowers on the canvas. This earned her the title 'Ballerina Girl' in the art circle.
- Currently a full-time student for BSc Psychology (3rd year standing) with 3.95 (out of 4.00) CGPA. Her academic standing has earned her Psi Chi membership, a peer tutor and mentor position in the academic support center, and a writing tutor at the writing center (only 3 are chosen from the entire university).

9. **Sub - 9**- The Strategic Visionary

This neural profile aligns with individuals who maintain calm yet responsive cognition under pressure, with internal clarity**,** emotional regulation, and a broad attentional field. These traits are commonly found in visionary leaders**,** public communicators, and serial entrepreneurs who integrate creativity with high performance.

- A famous YouTuber, entrepreneur, motivational speaker, and social media influencer who has had a remarkable journey of resilience and determination.
- Hosts one of India's top leadership podcasts with over 400 million yearly views. He is now a leading business content creator and motivational speaker who address global platforms like the United Nations and TedX.
- His business, Shamani Industries, boasts a turnover of ₹200 crore and a product portfolio that includes dishwashing liquids, soaps, detergents, and household cleaners. But his success didn't come without challenges.
- In the 1980s, his grandfather, father, and uncle migrated from Rajasthan to Indore in search of work. They initially sold coconuts on the streets, but later, Raj's father and uncle began working in a soap factory. By 1990, Raj's father launched the dishwasher brand Jadugar, which stabilized the family's financial situation.
- However, the 2008 recession dealt a blow to the business, and in 2013, Raj's father suffered a diabetic attack, leaving the family in severe financial distress. At just 16, Raj found himself at a crossroads. He wasn't academically inclined and struggled with public speaking, but the responsibility of supporting his family weighed heavily on him. Studying hard to get a job didn't seem like an option, so he turned to entrepreneurship.

10. **Sub - 10**- Embodied Mystic

This archetype represents individuals who demonstrate exceptional control over state regulation, shifting effortlessly between deep interceptive stillness and sharp somatosensory engagement. Common in seasoned yogis, meditation masters, or contemplative healers, this brain operates less like a conventional high-performance executive and more like a conscious gateway between body, breath, and consciousness.

- A certified Isha Hatha Yoga teacher, a disciple of Sadhguru, and the founder of a health and wellness enterprise that disseminates classical yogic practices
- She offers online and in-person yoga programs globally, working to make the benefits of classical Hatha Yoga accessible to more people.
- She was also a national swimming champion, indicating a background in rigorous physical training and discipline.

11. **Sub - 11**- The Mystical Integrator

This neural profile reflects an individual with deep contemplative absorption, profound internal coherence, and dynamic visual-spatial consciousness. While several markers fall outside conventional peak ranges, they align with advanced non-dual awareness**,** spiritual surrender, and psycho-physiological stillness — all of which are neuro-phenomenological validated in long-term mediators, sages, and mystics.

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- Shankaracharya devotee
- Advainta teacher
- Best astrologer in India

12. **Sub - 12**- The Internal Integrator

This archetype is marked by exceptional introspective awareness, volitional modulation of cortical rhythms, and multi-state switching capacity. The brain sustains high relaxation, gamma synchronization, and strong EC-EO adaptability — ideal for breath-based, meditative, or consciousness expansion practices. The Swara Yoga Master neural signature reflects not just peak performance in output tasks, but peak regulation of inner experience.

13. **Sub - 13**- The Visionary Achiever

This archetype reflects a mind that transforms adversity into acceleration. The profile shows a drive that is not born of entitlement but of discipline, persistence, and the will to rise above constraints. Neural patterns suggest a brain that thrives under challenge, shifting quickly from inward effort to outward execution. While there are traces of over activation linked to constant striving, these are balanced by remarkable adaptive mechanisms for recovery, clarity, and resilience.

- Self-reliance for paying student loans (part-time jobs) while pursuing a master's in London
- Arrived in Dubai debt-free and started with a decent salary as a Banker
- Ambition and resilience got him promotions at an age where that position is usually held by people 8-10 years older
- Earned a very good reputation as a banker and revered as an 'amazing boss' by his team
- Highly ambitious to reach great heights, driven by the motive to provide the best for his family

Experiments: Data and Analysis

Cluster 1
Cognitive Flexibility and Executive Functioning

Sub - A	**EEG Marker**	**EC Value**	**Benchmark- Peak Performer pool/ Std benchmark**	**EO Value**	**Benchmark- Peak Performer pool/ Std benchmark**
	Theta/Beta (Cz)	2.34	2.39 ±1.27/ 1.1-1.4	2.14	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	0.54	1.15 ±1.3/ 2.0-3.0	0.55	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	0.9	2.4 ±2.86/ 2.2-3.2	0.57	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	1.26	4.23 ±3.73/ 3.0-4.2	0.96	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.6	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= 2.0	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= 1.9	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation	54.95%	72.7 ±20.43%/ ≥30%		

Sub - B	**EEG Marker**	**EC Value**	**Benchmark- Peak Performer pool/ Std Benchmark**	**EO Value**	**Benchmark- Peak Performer pool/ Std Benchmark**
	Theta/Beta (Cz)	4.6	2.39 ±1.27/ 1.1-1.4	3.67	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	0.5	1.15 ±1.3/ 2.0-3.0	0.46	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	0.76	2.4 ±2.86/ 2.2-3.2	0.79	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	0.84	4.23 ±3.73/ 3.0-4.2	0.86	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.6	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= -1.9	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= -1.8	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	20.9%	72.7 ±20.43%/ ≥30%		

Sub - C	**EEG Marker**	**EC Value**	**Benchmark- Peak Performer pool/ Std Benchmark**	**EO Value**	**Benchmark- Peak Performer pool/ Std Benchmark**

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	Theta/Beta (Cz)	3.4	2.39 ±1.27/ 1.1-1.4	3.17	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	0.42	1.15 ±1.3/ 2.0-3.0	0.4	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	0.6	2.4 ±2.86/ 2.2-3.2	0.5	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	1.67	4.23 ±3.73/ 3.0-4.2	0.83	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.42	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= 1	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= 1	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	48.87%	72.7 ±20.43%/ ≥30%		

Sub - D	**EEG Marker**	**EC Value**	**Benchmark- Peak Performer pool/ Std Benchmark**	**EO Value**	**Benchmark- Peak Performer pool/ Std Benchmark**
	Theta/Beta (Cz)	2.82	2.39 ±1.27/ 1.1-1.4	2.1	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	1.0	1.15 ±1.3/ 2.0-3.0	0.48	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	1.82	2.4 ±2.86/ 2.2-3.2	0.52	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	1.82	4.23 ±3.73/ 3.0-4.2	0.54	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.5	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= 2.3	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= 5.2	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	77.13%	72.7 ±20.43%/ ≥30%		

Sub - E	**EEG Marker**	**EC Value**	**Benchmark- Peak Performer pool/ Std Benchmark**	**EO Value**	**Benchmark- Peak Performer pool/ Std Benchmark**
	Theta/Beta (Cz)	4.65	2.39 ±1.27/ 1.1-1.4	2.22	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	0.48	1.15 ±1.3/ 2.0-3.0	0.55	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	0.42	2.4 ±2.86/ 2.2-3.2	0.6	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	0.22	4.23 ±3.73/ 3.0-4.2	0.45	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.57	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= 1.6	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= 5.2	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	-281.97%	72.7 ±20.43%/ ≥30%		
Sub - F	**EEG Marker**	**EC Value**	**Benchmark- Peak Performer pool/ Std Benchmark**	**EO Value**	**Benchmark- Peak Performer pool/ Std Benchmark**
	Theta/Beta (Cz)	1.3	2.39 ±1.27/ 1.1-1.4	1.5	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	0.88	1.15 ±1.3/ 2.0-3.0	1.34	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	1.54	2.4 ±2.86/ 2.2-3.2	1.26	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	4.13	4.23 ±3.73/ 3.0-4.2	1.05	1.4 ±0.66/ 2.8-3.8

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	Focus/Attention Score	--	--	1.3	1.81 ±1.62/1.1-1.5
	Gamma Activity	Z= -1.6	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= 6.1	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	-42.62%	72.7 ±20.43%/ ≥30%		

Sub - G	EEG Marker	EC Value	Benchmark- Peak Performer pool/ Std Benchmark	EO Value	Benchmark- Peak Performer pool/ Std Benchmark
	Theta/Beta (Cz)	4.04	2.39 ±1.27/ 1.1-1.4	3.58	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	1.36	1.15 ±1.3/ 2.0-3.0	0.85	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	1.68	2.4 ±2.86/ 2.2-3.2	1.1	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	3.15	4.23 ±3.73/ 3.0-4.2	0.79	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.99	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z- 1.8	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= 3.2	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	70.88%	72.7 ±20.43%/		

Sub - H	EEG Marker	EC Value	Benchmark- Peak Performer pool/ Std Benchmark 1.1-1.4	EO Value	Benchmark- Peak Performer pool/ Std Benchmark
	Theta/Beta (Cz)	10.35	2.39 ±1.27/ 1.1-1.4	10.92	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	0.39	1.15 ±1.3/ 2.0-3.0	0.32	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	0.51	2.4 ±2.86/ 2.2-3.2	0.37	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	0.61	4.23 ±3.73/ 3.0-4.2	0.42	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.34	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= - 7.6	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= - 9.7	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	4.83%	72.7 ±20.43%/ ≥30%		

Sub - I	EEG Marker	EC Value	Benchmark- Peak Performer pool/ Std Benchmark	EO Value	Benchmark- Peak Performer pool/ Std Benchmark
	Theta/Beta (Cz)	5.65	2.39 ±1.27/ 1.1-1.4	5.92	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	0.41	1.15 ±1.3/2.0-3.0	0.41	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	0.62	2.4 ±2.86/ 2.2-3.2	0.41	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	1.39	4.23 ±3.73/ 3.0-4.2	0.65	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.41	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= 2.6	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= 3.6	Z = 2.45 ±2.83/ Z=
	Alpha Modulation S	50.81%	72.7 ±20.43%/		

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Sub - J	EEG Marker	EC Value	Benchmark- Peak Performer pool/ Std Benchmark	EO Value	Benchmark - Peak Performer pool/ Std Benchmark
	Theta/Beta (Cz)	4.95	2.39 ±1.27/ 1.1-1.4	2.7	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	1.03	1.15 ±1.3/ 2.0-3.0	0.77	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	1.53	2.4 ±2.86/ 2.2-3.2	1.7	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	2.37	4.23 ±3.73/ 3.0-4.2	1.35	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	1.06	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= 3.1	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= -1.7	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	59.83%	72.7 ±20.43%/ ≥30%		

Sub - K	EEG Marker	EC Value	Benchmark - Peak Performer pool/ Std Benchmark	EO Value	Benchmark- Peak Performer pool/ Std Benchmark
	Theta/ Beta (Cz)	2.43	2.39 ±1.27/ 1.1-1.4	2.7	2.3 ±1.43/ 1.2-1.6
	Alpha/ Theta	1.1	1.15 ±1.3/ 2.0-3.0	0.78	0.66 ±0.29/ 1.8-2.6
	Alpha/ Theta	3.2	2.4 ±2.86/ 2.2-3.2	0.47	1.7 ±2.71/ 2.0-2.8
	Alpha/ Theta (Pz)	10.5	4.23 ±3.73/ 3.0-4.2	2.09	1.4 ±0.66/ 2.8-3.8
	Focus/ Attenti	--	--	0.6	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= 2.1	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= 1.9	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation	79.82%	72.7 ±20.43%/ ≥30%		

Sub - L	EEG Marker	EC Value	Benchmark- Peak Performer pool/ Std Benchmark	EO Value	Benchmark- Peak Performer pool/ Std Benchmark
	Theta/Beta (Cz)	2.35	2.39 ±1.27/ 1.1-1.4	2.22	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	0.62	1.15 ±1.3/ 2.0-3.0	0.56	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	0.5	2.4 ±2.86/ 2.2-3.2	0.41	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	0.36	4.23 ±3.73/ 3.0-4.2	0.61	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.48	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= -4.1	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= -5.3	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	52.3%	72.7 ±20.43%/ ≥30%		

Sub - L	EEG Marker	EC Value	Benchmark- Peak Performer pool	EO Value	Benchmark- Peak Performer pool

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	Theta/Beta (Cz)	3.56	2.39 ±1.27/ 1.1-1.4	3.14	2.3 ±1.43/ 1.2-1.6
	Alpha/Theta (Fz)	0.56	1.15 ±1.3/ 2.0-3.0	0.42	0.66 ±0.29/ 1.8-2.6
	Alpha/Theta (Cz)	0.622	2.4 ±2.86/ 2.2-3.2	0.44	1.7 ±2.71/ 2.0-2.8
	Alpha/Theta (Pz)	3.87	4.23 ±3.73/ 3.0-4.2	1.45	1.4 ±0.66/ 2.8-3.8
	Focus/Attention Score	--	--	0.43	1.81 ±1.62/ 1.1-1.5
	Gamma Activity	Z= 5.1	Z = +2.2 ±1.52/ Z= 0.3-0.8	Z= 3.5	Z = 2.45 ±2.83/ Z= 0.4-1.0
	Alpha Modulation Score	55.05%	72.7 ±20.43%/ ≥30%		

Cluster 2: Emotional regulation and Stress resilience

Sub - A	**EEG Marker**	**EC Value**	**Benchmark- peak performers pool/ Std benchmark**	**EO value**	**Benchmark- peak performers pool/ Std benchmark**
	HiBeta	Z= 1.5	Z=2.4 ±0.8/ Z < 1.0	Z= 1.5	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	1.34	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	3.21	4.6 ±3.8/ ≥3.5	0.94	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	4.24	10.43 ±12.4/ ≤ 3.8

Sub - B	**EEG Marker**	**EC Value**	**Benchmark- peak performers pool**	**EO value**	**Benchmark- peak performers pool**
	HiBeta	Z= 0.2	Z=2.4 ±0.8/ Z < 1.0	Z= 0.3	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	1.3	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	3.13	4.6 ±3.8/ ≥3.5	1.94	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	44.22	10.43 ±12.4/ ≤ 3.8

Sub - C	**EEG Marker**	**EC Value**	**Benchmark- peak performers pool**	**EO value**	**Benchmark- peak performers pool**
	HiBeta	Z= 1.3	Z=2.4 ±0.8/ Z < 1.0	Z= -0.4	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	1.07	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	1.95	4.6 ±3.8/ ≥3.5	1.3	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	35.1	10.43 ±12.4/ ≤ 3.8

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Sub - D	EEG Marker	EC Value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std benchmark
	HiBeta	Z= 1.0	Z=2.4 ±0.8/ Z < 1.0	Z= 1.6	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	1.81	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	2.6	4.6 ±3.8/ ≥3.5	0.36	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	3.87	10.43 ±12.4/ ≤ 3.8

Sub - E	EEG Marker	EC Value	Benchmark- peak performers pool/ Std benchmark	EO Value	Benchmark- peak performers pool/ Std benchmark
	HiBeta	Z= 0.9	Z=2.4 ±0.8/ Z < 1.0	Z= 3.9	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	1.01	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	2.51	4.6 ±3.8/ ≥3.5	1.61	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	4.78	10.43 ±12.4/ ≤ 3.8

Sub - F	EEG Marker	EC Value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std benchmark
	HiBeta	Z= 1.0	Z=2.4 ±0.8/ Z < 1.0	Z= 4.0	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	1.2	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	2.76	4.6 ±3.8/ ≥3.5	1.81	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	3.5	10.43 ±12.4/ ≤ 3.8

Sub - I	EEG Marker	EC Value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std
	HiBeta	Z= 0.1	Z=2.4 ±0.8/ Z < 1.0	Z= -0.2	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	1.2	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	4.85	4.6 ±3.8/ ≥3.5	2.11	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	28.71	10.43 ±12.4/ ≤ 3.8

Sub - G	EEG Marker	EC Value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std

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	HiBeta	Z= 2.1	Z=2.4 ±0.8/ Z < 1.0	Z= 2.4	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	1.45	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	6.61	4.6 ±3.8/ ≥3.5	4.21	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	2.3	10.43 ±12.4/ ≤ 3.8

Sub - H	**EEG Marker**	**EC Value**	**Benchmark- peak performers pool/ Std benchmark**	**EO value**	**Benchmark- peak performers pool/ Std**
	HiBeta	Z= 1.2	Z=2.4 ±0.8/ Z < 1.0	Z= -0.7	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	0.64	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	0.67	4.6 ±3.8/ ≥3.5	2.47	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	8.77	10.43 ±12.4/ ≤ 3.8

Sub - J	**EEG Marker**	**EC Value**	**Benchmark- peak performers pool/ Std benchmark**	**EO value**	**Benchmark- peak performers**
	HiBeta	Z= 3.4	Z=2.4 ±0.8/ Z < 1.0	Z= 2.3	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	2.65	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	4.37	4.6 ±3.8/ ≥3.5	1.83	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	8.08	10.43 ±12.4/ ≤ 3.8

Sub - K	**EEG Marker**	**EC Value**	**Benchmark- peak performers**	**EO value**	**Benchmark- peak performers**
	HiBeta	Z= 2.6	Z=2.4 ±0.8/ Z < 1.0	Z= 1.8	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	1.4	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	7.51	4.6 ±3.8/ ≥3.5	1.78	1.7 ±1.32
	Stress resilience	--	--	4.0	10.43 ±12.4/ ≤ 3.8

Sub - L	EEG Marker	EC Value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std benchmark
	HiBeta	Z= -1.8	Z=2.4 ±0.8/ Z < 1.0	Z= -0.2	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	0.7	1.5 ±0.35/ 0.75–0.95

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	Alpha/Beta Ratio	2.44	4.6 ±3.8/ ≥3.5	0.69	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	7.48	10.43 ±12.4/ ≤ 3.8

Sub - L	EEG Marker	EC Value	Benchmark-peak performers pool/ Std	EO value	Benchmark-peak performers pool/ Std
	HiBeta	Z= 5.3	Z=2.4 ±0.8/ Z < 1.0	Z= 1.6	Z=2.3 ±1.3/ Z < 1.2
	Arousal Index	--	--	2.35	1.5 ±0.35/ 0.75–0.95
	Alpha/Beta Ratio	1.45	4.6 ±3.8/ ≥3.5	1.8	1.7 ±1.32/ ≥3.2
	Stress resilience	--	--	5.3	10.43 ±12.4/ ≤ 3.8

Cluster 3: Creative and Ideational Processing

Sub - A	EEG Marker	EC Value	Benchmark-peak performers pool/ Std benchmark	EO Value	Benchmark-peak performers/ Std benchmark
	Frontal Alpha Asymmetry	0.13	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	10 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	12.5 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	11.3 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	11.5 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= 2.0	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= 1.9	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - B	EEG Marker	EC Value	Benchmark-peak performers pool/ Std benchmark	EO Value	Benchmark-peak performers/ Std benchmark
	Frontal Alpha Asymmetry	-0.18	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	10.7 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	10.9 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	10.8 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	10.9 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= -1.9	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= -1.8	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - C	EEG Marker	EC Value	Benchmark-peak performers pool / Std benchmark	EO Value	Benchmark-peak performers/ Std benchmark
	Frontal Alpha Asymmetry	-0.05	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	10.2 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	8.8 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	11.5 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	11.3 Hz	11 ±1 Hz/ 11.4–12.5 Hz

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	Gamma Activity	Z= 1.0	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= 1.0	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - D	**EEG Marker**	**EC Value**	**Benchmark-peak performers pool/ Std benchmark**	**EO Value**	**Benchmark-peak performers/ Std benchmark**
	Frontal Alpha Asymmetry	0.13	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	11.5 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	12.9 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	11.2 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	7.3 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= 2.3	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= 5.2	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - E	**EEG Marker**	**EC Value**	**Benchmark-peak performers pool/ Std benchmark**	**EO Value**	**Benchmark-peak performers/ Std benchmark**
	Frontal Alpha Asymmetry	0.33	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	11.2 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	10.9 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	12.3 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	10.8 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= 1.6	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= 5.2	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - F	**EEG Marker**	**EC Value**	**Benchmark-peak performers pool/ Std benchmark**	**EO Value**	**Benchmark-peak performers/ Std benchmark**
	Frontal Alpha Asymmetry	-0.1	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	11.8 Hz	9.51 ±2.98 Hz/ 11.2–	12.5 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	11.7 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	12.3 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= -1.6	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= 6.1	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - G	**EEG Marker**	**EC Value**	**Benchmark-peak performers pool/ Std benchmark**	**EO Value**	**Benchmark-peak performers/ Std benchmark**
	Frontal Alpha Asymmetry	-0.2	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	9.6 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	9.5 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz

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	Alpha Peak (Posterior)	9.6 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	9.4 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= 1.8	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= 3.2	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - G Sub - H	EEG Marker	EC Value	Benchmark-peak performers pool/ Std benchmark	EO Value	Benchmark-peak performers/ Std benchmark
	Frontal Alpha Asymmetry	-0.14	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	12.6 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	7.7 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	9.1 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	9.7 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= -7.6	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= -9.7	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - I	EEG Marker	EC Value	Benchmark-peak performers pool/ Std benchmark	EO Value	Benchmark-peak performers/ Std benchmark
	Frontal Alpha Asymmetry	-0.05	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	9.7 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	9 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	10 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	9.6 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= 2.6	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= 3.6	Z = 2.45 ±2.83

Sub -J	EEG Marker	EC Value	Benchmark-peak performers pool/ Std benchmark	EO Value	Benchmark-peak performers/ Std benchmark
	Frontal Alpha Asymmetry	0.53	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	10.8 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	11.4 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	11 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	11.4 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= 3.1	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= -1.7	Z = 2.45 ±2.83/ Z = 0.4–1.0

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Sub - K	EEG Marker	EC Value	Benchmark-peak performers pool/ Std benchmark	EO Value	Benchmark-peak performers/ Std benchmark
	Frontal Alpha Asymmetry	-0.13	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	10.8 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	10.9 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	11 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	10.9 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= 2.1	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= 1.9	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - L	EEG Marker	EC Value	Benchmark-peak performers pool/ Std benchmark	EO Value	Benchmark-peak performers/ Std benchmark
	Frontal Alpha Asymmetry	-0.17	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	12.5 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	13 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	10.6 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	11 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= -4.1	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= -5.3	Z = 2.45 ±2.83/ Z = 0.4–1.0

Sub - L	EEG Marker	EC Value	Benchmark-peak performers pool/ Std benchmark	EO Value	Benchmark-peak performers/ Std benchmark
	Frontal Alpha Asymmetry	0.02	0 ±0.21/ +0.2 to +0.4	--	--
	Alpha Peak (Frontal)	10.5 Hz	9.51 ±2.98 Hz/ 11.2–12.2 Hz	10.2 Hz	10.9 ±1.3 Hz/ 10.8–11.8 Hz
	Alpha Peak (Posterior)	11.8 Hz	10.5 ±0.77 Hz/ 11.4–12.5 Hz	12.1 Hz	11 ±1 Hz/ 11.4–12.5 Hz
	Gamma Activity	Z= 5.1	Z = +2.2 ±1.52/ Z = 0.3–0.8	Z= 3.5	Z = 2.45 ±2.83/ Z = 0.4–1.0

Cluster 4: Recovery and Restoration Capacity

Sub - L	EEG Marker	EC value	Benchmark- peak performers pool/ Std	EO value	Benchmark-peak performers pool/ Std benchmark

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			benchmark		
	Delta	Z= 2.7	Z=3.2±1.4 / Z < 1.5	Z= 2.7	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	55.05 %	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	57.75	72.98 ±21.0/ ≥35	--	--

Sub - L	**EEG Marker**	**EC value**	**Benchmark- peak performers pool/ Std benchmark**	**EO value**	**Benchmark- peak performers pool/ Std benchmark**
	Delta	Z= 5.8	Z=3.2±1.4	Z= 3.4	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	52.3%	72.7 ±20.43% / ≥30%	--	--
	Sleep Efficiency score	58.1	72.98 ±21.0/ ≥35	--	--

Sub - K	**EEG Marker**	**EC Value**	**Benchmark- peak performers pool/ Std benchmark**	**EO value**	**Benchmark- peak performers pool/ Std benchmark**
	Delta	Z= 0.6	Z=3.2±1.4 / Z < 1.5	Z= 1.1	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	79.82 %	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	80.42	72.98 ±21.0/ ≥35	--	--

Sub -J	**EEG Marker**	**EC value**	**Benchmark- peak performers pool/ Std benchmark**	**EO value**	**Benchmark- peak performers pool/ Std benchmark**
	Delta	Z= 4.4	Z=3.2±1.4 / Z < 1.5	Z= 3.9	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	59.83 %	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	64.23	72.98 ±21.0/ ≥35	--	--

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Sub - I	EEG Marker	EC Value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std benchmark
	Delta	Z= 3.8	Z=3.2±1.4/ Z < 1.5	Z= 2.9	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	50.81%	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	54.61	72.98 ±21.0/ ≥35	--	--

Sub - J	EEG Marker	EC value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std benchmark
	Delta	Z= 2.0	Z=3.2±1.4/ Z < 1.5	Z= 3.7	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	4.83%	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	6.83	72.98 ±21.0/ ≥35	--	--

Sub - G	EEG Marker	EC value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std benchmark
	Delta	Z= 7.3	Z=3.2±1.4/ Z < 1.5	Z= 6.4	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	70.88%	72.7 ±20.43%	--	--
	Sleep Efficiency score	78.18	72.98 ±21.0/ ≥35	--	--

Sub - H	EEG Marker	EC value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std benchmark
	Delta	Z= 0.6	Z=3.2±1.4/ Z < 1.5	Z= 3.8	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	-42.62%	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	-42.02	72.98 ±21.0/ ≥35	--	--

Sub - E	EEG Marker	EC value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std benchmark
	Delta	Z= 4.6	Z=3.2±1.4/ Z < 1.5	Z= 6.4	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	-281.97%	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	-277.37	72.98 ±21.0/ ≥35	--	--

Sub - D	EEG Marker	EC value	Benchmark- peak performers pool/ Std benchmark	EO value	Benchmark- peak performers pool/ Std benchmark

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	Delta	Z= 3.9	Z=3.2±1.4/ Z < 1.5	Z= 3.6	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	77.13%	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	81.03	72.98 ±21.0/ ≥35	--	--

Sub - C	**EEG Marker**	**EC value**	**Benchmark- peak performers pool/ Std benchmark**	**EO value**	**Benchmark- peak performers pool/ Std benchmark**
	Delta	Z= 2.2	Z=3.2±1.4/ Z < 1.5	Z= 2.4	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	48.87%	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	51.07	72.98 ±21.0/ ≥35	--	--

Sub - B	**EEG Marker**	**EC value**	**Benchmark- peak performers pool/ Std benchmark**	**EO value**	**Benchmark- peak performers pool/ Std benchmark**
	Delta	Z= 6.1	Z=3.2±1.4/ Z < 1.5	Z= 5.8	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	20.9%	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	27	72.98 ±21.0/ ≥35	--	--

Sub - A	**EEG Marker**	**EC value**	**Benchmark- peak performers pool/ Std benchmark**	**EO value**	**Benchmark- peak performers pool/ Std benchmark**
	Delta	Z= 3.0	Z=3.2±1.4/ Z < 1.5	Z= 2.5	Z=2.34 ±1.28/ Z < 1.8
	Alpha Modulation	54.95%	72.7 ±20.43%/ ≥30%	--	--
	Sleep Efficiency score	57.95	72.98 ±21.0/ ≥35	--	--

Cluster 5: Neural Integration and Engagement Rhythm

Sub - A	**EEG Marker**	**EC Value**	**Benchmark- peak performers/ Std benchmark**	**EO value**	**Benchmark- peak performers/ Std benchmark**
	Posterior Dominant Rhythm	10 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	10.15 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	3.66	6.9 ±6.7/ ≥3.8	--	--
	Focus/Attention score	--	--	0.6	1.81 ±1.62/ 1.1–1.5

Sub - B	**EEG Marker**	**EC Value**	**Benchmark- peak performers/ Std benchmark**	**EO value**	**Benchmark- peak performers/ Std benchmark**
	Posterior Dominant Rhythm	9.9 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	10.85 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	2.86	6.9 ±6.7/ ≥3.8	--	--
	Focus/Attention score	--	--	0.6	1.81 ±1.62/ 1.1–1.5

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Sub - C	EEG Marker	EC Value	Benchmark- peak performers/ Std benchmark	EO value	Benchmark- peak performers/ Std benchmark
	Posterior Dominant Rhythm	11.4 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	10.7 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	2.91	6.9 ±6.7/ ≥3.8	--	--
	Focus/Attention score	--	--	0.42	1.81 ±1.62/ 1.1–1.5

Sub - D	EEG Marker	EC Value	Benchmark- peak performers/ Std benchmark	EO value	Benchmark- peak performers/ Std benchmark
	Posterior Dominant Rhythm	11.05 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	7.15 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	4.31	6.9 ±6.7/ ≥3.8	--	--
	Focus/Attention score	--	--	0.5	1.81 ±1.62/ 1.1–1.5

Sub - E	EEG Marker	EC Value	Benchmark- peak performers/ Std benchmark	EO value	Benchmark- peak performers/ Std benchmark
	Posterior Dominant Rhythm	11.85 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	8.15 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	1.6	6.9 ±6.7/ ≥3.8	--	--
	Focus/Attention score	--	--	0.57	1.81 ±1.62/ 1.1–1.5

Sub - F	EEG Marker	EC Value	Benchmark- peak performers/ Std benchmark	EO value	Benchmark- peak performers/ Std benchmark
	Posterior Dominant Rhythm	10.55 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	11.5 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	4.21	6.9 ±6.7/ ≥3.8	--	--
	Focus/Attention score	--	--	1.3	1.81 ±1.62/ 1.1–1.5

Sub - G	EEG Marker	EC Value	Benchmark- peak performers/ Std benchmark	EO value	Benchmark- peak performers/ Std benchmark
	Posterior Dominant Rhythm	9.6 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	9.3 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	13.46	6.9 ±6.7/ ≥3.8	--	--
	Focus/Attention score	--	--	0.99	1.81 ±1.62/ 1.1–1.5

Sub - G	EEG Marker	EC Value	Benchmark- peak performers/ Std benchmark	EO value	Benchmark- peak performers/ Std benchmark
	Posterior Dominant Rhythm	8.8 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	9.45 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	5.72	6.9 ±6.7/ ≥3.8	--	--

	Focus/ Attention score	--	--	0.34	1.81 ±1.62/ 1.1–1.5

Sub - I	**EEG Marker**	**EC Value**	**Benchmark- peak performers/ Std benchmark**	**EO value**	**Benchmark- peak performers/ Std benchmark**
	Posterior Dominant Rhythm	9.95 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	9.05 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	3.6	6.9 ±6.7/ ≥3.8	--	--
	Focus/ Attention score	--	--	0.41	1.81 ±1.62/ 1.1–1.5

Sub -J	**EEG Marker**	**EC Value**	**Benchmark- peak performers/ Std benchmark**	**EO value**	**Benchmark- peak performers/ Std benchmark**
	Posterior Dominant Rhythm	10.95 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	11.15 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	7.6	6.9 ±6.7/ ≥3.8	--	--
	Focus/ Attention score	--	--	1.06	1.81 ±1.62/ 1.1–1.5

Sub - K	**EEG Marker**	**EC Value**	**Benchmark- peak performers/ Std benchmark**	**EO value**	**Benchmark- peak performers/ Std benchmark**
	Posterior Dominant Rhythm	10.9 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	10.8 Hz1	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	16.2	6.9 ±6.7/ ≥3.8	--	--
	Focus/ Attention score	--	--	0.6	1.81 ±1.62/ 1.1–1.5

Sub - L	**EEG Marker**	**EC Value**	**Benchmark- peak performers/ Std benchmark**	**EO value**	**Benchmark- peak performers/ Std benchmark**
	Posterior Dominant Rhythm	10.5 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	10.9 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	1.67	6.9 ±6.7/ ≥3.8	--	--
	Focus/ Attention score	--	--	0.48	1.81 ±1.62/ 1.1–1.5
Sub M	**EEG Marker**	**EC Value**	**Benchmark- peak performers/ Std benchmark**	**EO value**	**Benchmark- peak performers/ Std benchmark**
	Posterior Dominant Rhythm	10.35 Hz	10.2 ±1 Hz/ 11.5–12.5 Hz	10.25 Hz	10.1 ±1.02 Hz/ 11.0–12.0 Hz
	Relaxation score	7.46	6.9 ±6.7/ ≥3.8	--	--
	Focus/ Attention score	--	--	0.43	1.81 ±1.62/ 1.1–1.5

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1. Sub - A

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark-Peak Performers	EC: Std Benchmark- Peak Performers	EO: Value, region, and Broadmann Area	EO: Benchmark- Peak Performers	EO: Std Benchmark- Peak Performers
Alpha Peak (Frontal - highest)	10 Hz at F7 and F4	9.51 ±2.98 Hz	11.2–12.2 Hz	12.5 Hz at F4	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	11.3 Hz at P4	10.5 ±0.77 Hz	11.4–12.5 Hz	11.5 Hz at P4	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	0.13	0 ±0.21	+0.2 to +0.4			+0.1 to +0.3
Theta/Beta Ratio (Fz)	1.61- BA9	3.82 ±2	1.0–1.5		3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	2.34- BA6	2.39 ±1.27	1.1–1.4	2.14	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	0.54- BA9	1.15 ±1.3	2.0–3.0	0.55	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	0.9- BA6	2.4 ±2.86	2.2–3.2	0.57	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	1.26- BA7		4.23 ±3.73	3.0–4.2	0.96	1.4 ±0.66
Arousal Index ((Beta+HiBeta)/Alpha at Cz)					1.34	1.5 ±0.35
Excessive Beta/HiBeta	Z=1.8 (Beta at FP2), Z=1.5 (HiBeta at FP2)		Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z=2 (Beta at FP2), Z=1.5 at F4	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3
Alpha/Beta Ratio (Frontal-Parietal avg)	3.21		4.6 ±3.8	≥3.5	0.94	1.7 ±1.32
Excessive Delta	Z=3.0 at P3		Z=3.2±1.4	Z < 1.5	Z=2.5 at P3	Z=2.34 ±1.28
Posterior Dominant Rhythm	10 Hz		10.2 ±1	11.5–12.5 Hz	10.15 Hz	10.1 ±1.02
Relaxation Score (Alpha/Beta at Pz)	3.66		6.9 ±6.7	≥3.8		
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)					0.6	1.81 ±1.62
Gamma Activity	Z=2 at Frontal lobe- mid frontal gyrus- BA8		Z = +2.2 ±1.52	Z = 0.3–0.8	Z=1.9 at Parietal lobe- Precuneus - BA7	Z = 2.45 ±2.83
Alpha modulation score	54.95%		72.7 ±20.43%	≥30%		
Sleep efficiency score	57.95		75.86 ±20.26	≥35		

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Stress resilience				4.24	10.43 ±12.4	≤ 3.8

2. **Sub - B**

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark- Peak Performers	EC: Std Benchmark- Peak Performers	EO: Value, region , and Broadmann Area	EO: Benchmark- Peak Performers	EO: Std Benchmark- Peak Performers
Alpha Peak (Frontal - highest)	10.7 Hz at Fz	9.51 ±2.98 Hz	11.2–12.2 Hz	10.9 Hz at Fz	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	10.8 Hz at Pz and O1	10.5 ±0.77 Hz	11.4–12.5 Hz	10.9 Hz at P3, P4, and O2	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	-0.18	0 ±0.21	+0.2 to +0.4			+0.1 to +0.3
Theta/Beta Ratio (Fz)	4.6- BA9	3.82 ±2	1.0–1.5	4.98	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	4.6- BA6	2.39 ±1.27	1.1–1.4	3.67	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	0.5- BA9	1.15 ±1.3	2.0–3.0	0.46	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	0.76- BA6	2.4 ±2.86	2.2–3.2	0.79	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	0.84- BA7	4.23 ±3.73	3.0–4.2	0.86	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/ Alpha at Cz)				1.3	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=-0.2 (Beta at Pz), Z=0.2 (HiBeta at Pz)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z= 0.4 (Beta at T4), Z= 0.3 (HiBeta at Pz)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	3.13	4.6 ±3.8	≥3.5	1.94	1.7 ±1.32	≥3.2
Excessive Delta	Z=6.1 at P3	Z=3.2±1.4	Z < 1.5	Z=5.8 at P3	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	9.9 Hz	10.2 ±1	11.5–12.5 Hz	10.85 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	2.86	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.6	1.81 ±1.62	1.1–1.5
Gamma Activity	Z= -1.9 at Limbic lobe-posterior	Z = +2.2 ±1.52	Z = 0.3–0.8	Z= -1.8 at Sub-lobar-	Z = 2.45 ±2.83	Z = 0.4–1.0

	cingulate-BA23			insula-BA13		
Alpha modulation score	20.9%	72.7 ±20.43%	≥30%			
Sleep efficiency score	27	72.98 ±21.0	≥35			
Stress resilience				44.22	10.43 ±12.4	≤ 3.8

3. **Sub - I**

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark-Peak Performers	EC: Std Benchmark-Peak Performers	EO: Value, region, and Broadmann Area	EO: Benchmark-Peak Performers	EO: Std Benchmark-Peak Performers
Alpha Peak (Frontal - highest)	9.7 Hz at FP2	9.51 ±2.98 Hz	11.2–12.2 Hz	9 Hz at FP1	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	10 Hz at O1	10.5 ±0.77 Hz	11.4–12.5 Hz	9.6 Hz at O2	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	-0.05	0 ±0.21	+0.2 to +0.4			+0.1 to +0.3
Theta/Beta Ratio (Fz)	6.02- BA9	3.82 ±2	1.0–1.5	4.97	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	5.65- BA6	2.39 ±1.27	1.1–1.4	5.92	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	0.41- BA9	1.15 ±1.3	2.0–3.0	0.41	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	0.62- BA6	2.4 ±2.86	2.2–3.2	0.41	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	1.39- BA7	4.23 ±3.73	3.0–4.2	0.65	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/Alpha at Cz)				1.2	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z= 0.7 (Beta at O2), Z= -0.1 (HiBeta at O2)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z= -0.1 (Beta at O2), Z= -0.2 (HiBeta at O2)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	4.85	4.6 ±3.8	≥3.5	2.11	1.7 ±1.32	≥3.2
Excessive Delta	Z=3.8 at O2	Z=3.2±1.4	Z < 1.5	Z=2.9 at O2	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	9.95 Hz	10.2 ±1	11.5–12.5 Hz	9.05 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	3.6	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta				0.41	1.81 ±1.62	1.1–1.5

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at Fz, Pz, + Abs Theta)						
Gamma Activity	Z=2.6 at Parietal lobe-postcentral gyrus- BA7	Z = +2.2±1.52	Z = 0.3–0.8	Z=3.6 at Parietal lobe-precuneus-BA7	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	50.81%	72.7 ±20.43%	≥30%			
Sleep efficiency score	54.61	72.98 ±21.0	≥35			
Stress resilience				28.71	10.43 ±12.4	≤ 3.8

4. **Sub - C**

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark-Peak Performers	EC: Std Benchmark-Peak Performers	EO: Value, region, and Broadmann Area	EO: Benchmark-Peak Performers	EO: Std Benchmark-Peak Performers
Alpha Peak (Frontal - highest)	10.2 Hz at FP1 and F8	9.51 ±2.98 Hz	11.2–12.2 Hz	8.8 Hz at F4	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	11.5 at O1	10.5 ±0.77 Hz	11.4–12.5 Hz	11.3 Hz at Pz	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	-0.05	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	4.42-BA9	3.82 ±2	1.0–1.5	3.99	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	3.4-BA6	2.39 ±1.27	1.1–1.4	3.17	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	0.42-BA9	1.15 ±1.3	2.0–3.0	0.4	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	0.6-BA6	2.4 ±2.86	2.2–3.2	0.5	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	1.67-BA7	4.23 ±3.73	3.0–4.2	0.83	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/Alpha at Cz)				1.07	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=1.6 (Beta at FP1), Z=1.3 (HiBeta at FP1)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z=1.2 (Beta at Fz), Z= -0.4 (HiBeta at Fz)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	1.95	4.6 ±3.8	≥3.5	1.3	1.7 ±1.32	≥3.2

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Excessive Delta	Z=2.2 at C4	Z=3.2±1.4	Z < 1.5	Z=2.4 at C4	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	11.4 Hz	10.2 ±1	11.5–12.5 Hz	10.7 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	2.91	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.42	1.81 ±1.62	1.1–1.5
Gamma Activity	Z=1 at limbic lobe-anterior cingulate-BA32	Z = +2.2 ±1.52	Z = 0.3–0.8	Z=1 at limbic lobe- anterior cingulate- BA32	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	48.87 %	72.7 ±20.43%	≥30%			
Sleep efficiency score	51.07	72.98 ±21.0	≥35			
Stress resilience				35.1	10.43 ±12.4	≤ 3.8

5. **Sub - D**

EEG Marker	**EC: Value, region, and Brodmann Area**	**EC: Benchmark- Peak Performers**	**EC: Std Benchmark- Peak Performers**	**EO: Value, region, and Broadmann Area**	**EO: Benchmark- Peak Performers**	**EO: Std Benchmark- Peak Performers**
Alpha Peak (Frontal - highest)	11.5 Hz at F8	9.51 ±2.98 Hz	11.2–12.2 Hz	12.9 Hz at F4	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	11.2 Hz at P3 and O1	10.5 ±0.77 Hz	11.4–12.5 Hz	7.3 Hz at O2	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	0.13	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	3.23- BA9	3.82 ±2	1.0–1.5	1.4	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	2.82- BA6	2.39 ±1.27	1.1–1.4	2.1	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	1.0- BA9	1.15 ±1.3	2.0–3.0	0.48	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	1.82- BA6	2.4 ±2.86	2.2–3.2	0.52	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	1.82- BA7	4.23 ±3.73	3.0–4.2	0.54	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta) /Alpha at Cz)				1.81	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z= 1.7 (Beta at FP1),	Beta: Z=2.3 ±1	Beta and HiBeta: Z < 1.0	Z=2.5 (Beta at FP2),	Beta: Z=2 ±1.5	Beta and HiBeta: Z < 1.2

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	Z=1 (HiBeta at FP1)	HiBeta: Z=2.4 ±0.8		Z=1.6 (HiBeta at FP2)	HiBeta: Z=2.3 ±1.3	
Alpha/Beta Ratio (Frontal-Parietal avg)	2.6	4.6 ±3.8	≥3.5	0.36	1.7 ±1.32	≥3.2
Excessive Delta	Z=3.9 at P3	Z=3.2±1.4	Z < 1.5	Z=3.6 at P3	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	11.05 Hz	10.2 ±1	11.5–12.5 Hz	7.15 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	4.31	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.5	1.81 ±1.62	1.1–1.5
Gamma Activity	Z=2.3 at parietl lobe-postcentral gyrus-BA7	Z = +2.2 ±1.52	Z = 0.3–0.8	Z=5.2 at frontal lobe-paracentral lobule-BA5	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	77.13%	72.7 ±20.43%	≥30%			
Sleep efficiency score	81.03	72.98 ±21.0	≥35			
Stress resilience				3.87	10.43 ±12.4	≤ 3.8

6. **Sub - E**

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark- Peak Performers	EC: Std Benchmark- Peak Performers	EO: Value, region, and Broadman Area	EO: Benchmark- Peak Performers	EO: Std Benchmark- Peak Performers
Alpha Peak (Frontal - highest)	11.2 Hz at F8	9.51 ±2.98 Hz	11.2–12.2 Hz	10.9 Hz at Fz	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	12.3 Hz at O1	10.5 ±0.77 Hz	11.4–12.5 Hz	10.8 Hz at P3	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	0.33	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	3.23-BA9	3.82 ±2	1.0–1.5	2.3	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	4.65-BA6	2.39 ±1.27	1.1–1.4	2.22	2.3±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	0.48-BA9	1.15 ±1.3	2.0–3.0	0.55	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	0.42-BA6	2.4 ±2.86	2.2–3.2	0.6	1.7 ±2.71	2.0–2.8

Alpha/Theta Ratio (Pz)	0.22-BA7	4.23 ±3.73	3.0–4.2	0.45	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/Alpha at Cz)				1.01	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=1.1 (Beta at F3), Z=0.9 (HiBeta at P3)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z=4.8 (Beta at Fz), Z=3.9 (HiBeta at Fz)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	2.51	4.6 ±3.8	≥3.5	1.61	1.7 ±1.32	≥3.2
Excessive Delta	Z=4.6 at Pz	Z=3.2 ±1.4	Z < 1.5	Z=6.4 at Pz	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	11.85 Hz	10.2 ±1	11.5–12.5 Hz	8.15 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	1.6	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.57	1.81 ±1.62	1.1–1.5
Gamma Activity	Z=1.6 at parietal lobe-postcentral gyrus-BA7	Z = +2.2 ±1.52	Z = 0.3–0.8	Z=5.2 at parietal lobe-postcentral gyrus-BA7	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	-281.97%	72.7 ±20.43 %	≥30%			
Sleep efficiency score	-277.37	72.98 ±21.0	≥35			
Stress resilience		3.04 ±3.5	≤ 3.5	4.78	10.43 ±12.4	≤ 3.8

7. Sub - F

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark- Peak Performers	EC: Std Benchmark- Peak Performers	EO: Value, region, and	EO: Benchmark- Peak Performers	EO: Std Benchmark- Peak Performers

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				Broadmann Area		
Alpha Peak (Frontal - highest)	11.8 Hz at F4	9.51 ±2.98 Hz	11.2–12.2 Hz	12.5 Hz at FP1	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	11.7 Hz at P3 and P4	10.5 ±0.77 Hz	11.4–12.5 Hz	12.3 Hz at P4	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	-0.1	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	1.82-BA9	3.82 ±2	1.0–1.5	1.6	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	1.3- BA6	2.39 ±1.27	1.1–1.4	1.5	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	0.88-BA9	1.15 ±1.3	2.0–3.0	1.34	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	1.54-BA6	2.4 ±2.86	2.2–3.2	1.26	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	4.13-BA7	4.23 ±3.73	3.0–4.2	1.05	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/ Alpha at Cz)				1.2	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=1 (Beta at FP2), Z=1 (HiBeta at FP2)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z=3.8 (Beta at Fz), Z=4 (HiBeta at Pz)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	2.76	4.6 ±3.8	≥3.5	1.81	1.7 ±1.32	≥3.2
Excessive Delta	Z=0.6 at C3	Z=3.2±1.4	Z < 1.5	Z=3.8 at Pz	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	10.55 Hz	10.2 ±1	11.5–12.5 Hz	11.5 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	4.21	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				1.3	1.81 ±1.62	1.1–1.5
Gamma Activity	Z- -1.6 at temporal lobe-inferior	Z = +2.2 ±1.52	Z = 0.3–0.8	Z=6.1-superior	Z = 2.45 ±2.83	Z = 0.4–1.0

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	temporal gyrus-BA20			lobe - parietal superior lobule-BA7		
Alpha modulation score	-42.62	72.7 ±20.43%	≥30%			
Sleep efficiency score	-42.02	72.98 ±21.0	≥35			
Stress resilience				3.5	10.43 ±12.4	≤ 3.8

8. **Sub - G**

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark-Peak Performers	EC: Std Benchmark-Peak Performers	EO: Value, region, and Broadmann Area	EO: Benchmark-Peak Performers	EO: Std Benchmark- Peak Performers
Alpha Peak (Frontal - highest)	9.6 Hz at FP1	9.51 ±2.98 Hz	11.2–12.2 Hz	9.5 Hz at FP1 and Fz	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	9.6 Hz at Pz, O1, and O2	10.5 ±0.77 Hz	11.4–12.5 Hz	9.4 Hz at P3 and P4	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	-0.2	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	3.31- BA9	3.82 ±2	1.0–1.5	2.71	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	4.04- BA6	2.39 ±1.27	1.1–1.4	3.58	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	1.36- BA9	1.15 ±1.3	2.0–3.0	0.85	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	1.68- BA6	2.4 ±2.86	2.2–3.2	1.1	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	3.15- BA7	4.23 ±3.73	3.0–4.2	0.79	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/Alpha at Cz)				1.45	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=1.9 (Beta at FP1), Z=2.1 (HiBeta at F3)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z=2.1 (Beta at F3), Z=2.4 (HiBeta at F3)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	6.61	4.6 ±3.8	≥3.5	4.21	1.7 ±1.32	≥3.2
Excessive Delta	Z=7.3 at Cz	Z=3.2±1.4	Z < 1.5	Z=6.4 at Pz	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	9.6 Hz	10.2 ±1	11.5–12.5 Hz	9.3 Hz	10.1 ±1.02	11.0–12.0 Hz

Relaxation Score (Alpha/Beta at Pz)	13.46	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.99	1.81 ±1.62	1.1–1.5
Gamma Activity	Z=1.8 at parietal lobe-postcentral gyrus- BA5	Z = +2.2 ±1.52	Z = 0.3–0.8	Z=3.2 at parietal lobe-precuneus-BA7	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	70.88%	72.7 ±20.43%	≥30%			
Sleep efficiency score	78.18	72.98 ±21.0	≥35			
Stress resilience				2.3	10.43 ±12.4	≤ 3.8

9. **Sub - G**

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark-Peak Performer	EC: Std Benchmark-Peak Performers	EO: Value, region, and Broadmann Area	EO: Benchmark-Peak Performer	EO: Std Benchmark-Peak Performers
Alpha Peak (Frontal - highest)	12.6 Hz at FP2	9.51 ±2.98 Hz	11.2–12.2 Hz	7.7 Hz at FP2	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	9.1 Hz at P4	10.5 ±0.77 Hz	11.4–12.5 Hz	9.7 Hz at O1	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	-0.14	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	10.73- BA9	3.82 ±2	1.0–1.5	9.98	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	10.35- BA6	2.39 ±1.27	1.1–1.4	10.92	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	0.39- BA9	1.15 ±1.3	2.0–3.0	0.32	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	0.51- BA6	2.4 ±2.86	2.2–3.2	0.37	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	0.61- BA7	4.23 ±3.73	3.0–4.2	0.42	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/Alpha at Cz)				0.64	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=2.2 (Beta at F8), Z=1.2 (HiBeta at F8)	Beta: Z=2.3 ±1 HiBeta : Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z= -0.2 (Beta at T4), Z= -0.7 (HiBeta at T4)	Beta: Z=2 ±1.5 HiBeta : Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	0.67	4.6 ±3.8	≥3.5	2.47	1.7 ±1.32	≥3.2
Excessive Delta	Z=2 at C3	Z=3.2± 1.4	Z < 1.5	Z=3.7 at C3	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	8.8 Hz	10.2 ±1	11.5–12.5 Hz	9.45 Hz	10.1 ±1.02	11.0–12.0 Hz

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Relaxation Score (Alpha/Beta at Pz)	5.72	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.34	1.81 ±1.62	1.1–1.5
Gamma Activity	Z= -7.6 at limbic lobe-cingulate gyrus- BA23	Z = +2.2±1 .52	Z = 0.3–0.8	Z= -9.7 at limbic lobe-cingulate gyrus-BA23	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	4.83%	72.7 ±20.43 %	≥30%			
Sleep efficiency score	6.83	72.98 ±21.0	≥35			
Stress resilience				8.77	10.43 ±12.4	≤ 3.8

10. **Sub - L**

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark- Peak Performers	EC: Std Benchmark- Peak Performers	EO: Value, region, and Broadmann Area	EO: Benchmark-Peak Performers	EO: Std Benchmark- Peak Performers
Alpha Peak (Frontal - highest)	10.5 Hz at FP2 and F8	9.51 ±2.98 Hz	11.2–12.2 Hz	10.2 Hz at F7	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	11.8 Hz at P4	10.5 ±0.77 Hz	11.4–12.5 Hz	12.1 Hz at P4	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	0.02	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	2.99- BA9	3.82 ±2	1.0–1.5	3.22	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	3.56- BA6	2.39 ±1.27	1.1–1.4	3.14	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	0.56- BA9	1.15 ±1.3	2.0–3.0	0.42	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	0.62- BA6	2.4 ±2.86	2.2–3.2	0.44	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	3.87- BA7	4.23 ±3.73	3.0–4.2	1.45	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta) /Alpha at Cz)				2.35	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=5 (Beta at FP2), Z=5.3 (HiBeta at FP2)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z=1.4 (Beta at FP2), Z=1.6 (HiBeta at FP2)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	1.45	4.6 ±3.8	≥3.5	1.8	1.7 ±1.32	≥3.2

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Excessive Delta	Z=2.7 at Cz	Z=3.2±1.4	Z < 1.5	Z=2.7 at Cz	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	10.35	10.2 ±1	11.5–12.5 Hz	10.25 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	7.46	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.43	1.81 ±1.62	1.1–1.5
Gamma Activity	Z=5.1 at limbic lobe- anterior cingulate- BA24	Z = +2.2 ±1.52	Z = 0.3–0.8	Z=3.5 at frontal lobe- paracentral lobule- BA5	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	55.05%	72.7 ±20.43%	≥30%			
Sleep efficiency score	57.75	72.98 ±21.0	≥35			
Stress resilience				5.3	10.43 ±12.4	≤ 3.8

11. **Sub -J**

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark- Peak Performers	EC: Std Benchmark- Peak Performers	EO: Value, region, and Broadman Area	EO: Benchmark- Peak Performers	EO: Std Benchmark- Peak Performers
Alpha Peak (Frontal - highest)	10.8 Hz at FP1 and F8	9.51 ±2.98 Hz	11.2–12.2 Hz	11.4 at FP2	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	11 Hz at O2	10.5 ±0.77 Hz	11.4–12.5 Hz	11.4 at P3	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	0.53	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	3.47- BA9	3.82 ±2	1.0–1.5	3.3	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	4.95- BA6	2.39 ±1.27	1.1–1.4	2.7	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	1.03- BA9	1.15 ±1.3	2.0–3.0	0.77	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	1.53- BA6	2.4 ±2.86	2.2–3.2	1.7	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	2.37- BA7	4.23 ±3.73	3.0–4.2	1.35	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/Alpha at Cz)				2.65	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=4 (Beta at FP1), Z=3.4	Beta: Z=2.3 ±1	Beta and HiBeta: Z < 1.0	Z=2.3 (Beta at FP1),	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2

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	(HiBeta at FP1)	HiBeta: Z=2.4 ±0.8		Z=1.5 (HiBeta at FP1)		
Alpha/Beta Ratio (Frontal-Parietal avg)	4.37	4.6 ±3.8	≥3.5	1.83	1.7 ±1.32	≥3.2
Excessive Delta	Z=4.4 at T3	Z=3.2±1.4	Z < 1.5	Z=3.9 at T5	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	10.95 Hz	10.2 ±1	11.5–12.5 Hz	11.15 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	7.6	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				1.06	1.81 ±1.62	1.1–1.5
Gamma Activity	Z=3.1 at frontal lobe-medial frontal gyrus-BA10	Z = +2.2 ±1.52	Z = 0.3–0.8	Z= -1.7 at occipital lobe-middle occipital gyrus-BA19	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	59.83%	72.7 ±20.43%	≥30%			
Sleep efficiency score	64.23	72.98 ±21.0	≥35			
Stress resilience				8.08	10.43 ±12.4	≤ 3.8

12. **Sub - L**

EEG Marker	**EC: Value, region, and Brodmann Area**	**EC: Benchmark-Peak Performers**	**EC: Std Benchmark-Peak Performers**	**EO: Value, region, and Broadmann Area**	**EO: Benchmark-Peak Performers**	**EO: Std Benchmark-Peak Performers**
Alpha Peak (Frontal - highest)	12.5 Hz at F3	9.51 ±2.98 Hz	11.2–12.2 Hz	13 Hz at FP1	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	10.6 at P3	10.5 ±0.77 Hz	11.4–12.5 Hz	11 Hz at O2	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	-0.17	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	1.94- BA9	3.82 ±2	1.0–1.5	1.17	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	2.35- BA6	2.39 ±1.27	1.1–1.4	2.22	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	0.62- BA9	1.15 ±1.3	2.0–3.0	0.56	0.66 ±0.29	1.8–2.6

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Alpha/Theta Ratio (Cz)	0.5- BA6	2.4 ±2.86	2.2–3.2	0.41	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	0.36- BA7	4.23 ±3.73	3.0–4.2	0.61	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/Alpha at Cz)				0.7	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=0.8 (Beta at T4), Z=-1.8 (HiBeta at Pz)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z=0.9 (Beta at FP1), Z= -0.2 (HiBeta at FP1)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	2.44	4.6 ±3.8	≥3.5	0.69	1.7 ±1.32	≥3.2
Excessive Delta	Z=5.8 at P4	Z=3.2±1.4	Z < 1.5	Z=3.5 at P4	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	10.5 Hz	10.2 ±1	11.5–12.5 Hz	10.9 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	1.67	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.48	1.81 ±1.62	1.1–1.5
Gamma Activity	Z= -4.1 at limbic lobe-cingulate gyrus-BA23	Z = +2.2 ±1.52	Z = 0.3–0.8	Z= -5.3 at limbic lobe-cingulate gyrus-BA31	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	52.3%	72.7 ±20.43%	≥30%			
Sleep efficiency score	58.1	72.98 ±21.0	≥35			
Stress resilience				7.48	10.43 ±12.4	≤ 3.8

13. **Sub - K**

EEG Marker	**EC: Value, region, and Brodmann Area**	**EC: Benchmark-Peak Performers**	**EC: Std Benchmark-Peak Performers**	**EO: Value, region, and Broadmann Area**	**EO: Benchmark- Peak Performers**	EO: Std Benchmark- Peak Performers
Alpha Peak (Frontal - highest)	10.8 Hz atFP1	9.51 ±2.98 Hz	11.2–12.2 Hz	10.9 Hz at FP1	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	11 at O1	10.5 ±0.77 Hz	11.4–12.5 Hz	10.9 Hz at P3	11 ±1	11.0–12.0 Hz

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Frontal Alpha Asymmetry	-0.13	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	2.78- BA9	3.82 ±2	1.0–1.5	2.85	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	2.43- BA6	2.39 ±1.27	1.1–1.4	2.7	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	1.1- BA9	1.15 ±1.3	2.0–3.0	0.78	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	3.2- BA6	2.4 ±2.86	2.2–3.2	0.47	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	10.5- BA7	4.23 ±3.73	3.0–4.2	2.09	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/Alpha at Cz)				1.4	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=3.3 (Beta at FP1), Z=2.6 (HiBeta at FP1)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z=1.8 (Beta at FP1), Z=1.8 (HiBeta at F7)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	7.51	4.6 ±3.8	≥3.5	1.78	1.7 ±1.32	≥3.2
Excessive Delta	Z=0.6 at O2	Z=3.2±1.4	Z < 1.5	Z=1.1 at T4	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	10.9 Hz	10.2 ±1	11.5–12.5 Hz	10.8 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	16.2	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.6	1.81 ±1.62	1.1–1.5
Gamma Activity	Z= 2.1 at frontal lobe- medial frontal gyrus- BA10	Z = +2.2±1.52	Z = 0.3–0.8	Z= 1.9 at frontal lobe- inferior frontal gyrus- BA45	Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	79.82	72.7 ±20.43%	≥30%			
Sleep efficiency score	80.42	72.98 ±21.0	≥35			
Stress resilience				4	10.43 ±12.4	≤ 3.8

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14. Vikas

EEG Marker	EC: Value, region, and Brodmann Area	EC: Benchmark- Peak Performers	EC: Std Benchmark- Peak Performers	EO: Value, region, and Broadmann Area	EO: Benchmark- Peak Performers	EO: Std Benchmark- Peak Performers
Alpha Peak (Frontal - highest)	10.8 Hz atFP2 and Fz	9.51 ±2.98 Hz	11.2–12.2 Hz	13 Hz at FP2, Fz, and F4	10.9 ±1.3	10.8–11.8 Hz
Alpha Peak (Posterior - highest)	10.1 at O1	10.5 ±0.77 Hz	11.4–12.5 Hz	12.3 Hz at O1	11 ±1	11.0–12.0 Hz
Frontal Alpha Asymmetry	0.083	0 ±0.21	+0.2 to +0.4			
Theta/Beta Ratio (Fz)	0.89-BA9	3.82 ±2	1.0–1.5	1.5	3.14 ±1.63	1.1–1.6
Theta/Beta Ratio (Cz)	0.68-BA6	2.39 ±1.27	1.1–1.4	0.88	2.3 ±1.43	1.2–1.6
Alpha/Theta Ratio (Fz)	1.7-BA9	1.15 ±1.3	2.0–3.0	0.83	0.66 ±0.29	1.8–2.6
Alpha/Theta Ratio (Cz)	2.22-BA6	2.4 ±2.86	2.2–3.2	0.9	1.7 ±2.71	2.0–2.8
Alpha/Theta Ratio (Pz)	4.16-BA7	4.23 ±3.73	3.0–4.2	1.5	1.4 ±0.66	2.8–3.8
Arousal Index ((Beta+HiBeta)/Alpha at Cz)				0.62	1.5 ±0.35	0.75–0.95
Excessive Beta/HiBeta	Z=4.9 (Beta at Fz), Z=4 (HiBeta at Fz)	Beta: Z=2.3 ±1 HiBeta: Z=2.4 ±0.8	Beta and HiBeta: Z < 1.0	Z=2.3 (Beta at O1), Z=3.8 (HiBeta at O1)	Beta: Z=2 ±1.5 HiBeta: Z=2.3 ±1.3	Beta and HiBeta: Z < 1.2
Alpha/Beta Ratio (Frontal-Parietal avg)	3.78	4.6 ±3.8	≥3.5	0.96	1.7 ±1.32	≥3.2
Excessive Delta	Z=5.4 at P4	Z=3.2±1.4	Z < 1.5	Z=2.4 at P4	Z=2.34 ±1.28	Z < 1.8
Posterior Dominant Rhythm	10.05 Hz	10.2 ±1	11.5–12.5 Hz	11.65 Hz	10.1 ±1.02	11.0–12.0 Hz
Relaxation Score (Alpha/Beta at Pz)	16.2	6.9 ±6.7	≥3.8			
Focus/Attention Score (avg of Theta/Beta at Fz, Pz, + Abs Theta)				0.86	1.81 ±1.62	1.1–1.5

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Gamma Activity		Z = +2.2 ±1.52	Z = 0.3–0.8		Z = 2.45 ±2.83	Z = 0.4–1.0
Alpha modulation score	94.72%	72.7 ±20.43%	≥30%			
Sleep efficiency score	99.62	72.98 ±21.0	≥35			
Stress resilience				1	10.43 ±12.4	≤ 3.8

Concluding Remark

Understanding peak performance requires piecing together intricate electrical rhythms of brain and identifying patterns that distinguish exceptional individuals from typical functioning. Paper aims to comprehend quantitative electroencephalography (QEEG) to uncover neurophysiological underpinnings of peak performers. Paper adopts EEG traits include frontal alpha modulation, sensorimotor rhythm regulation, and inter-regional coherence that serve as foundational markers of peak performance. These patterns are observed during resting states, reinforcing that peak performance is product of enduring neurophysiological configurations rather than transient mental states. Paper explores how individuals regulate attention, integrate sensory input and adaptively respond to changing demands by capturing oscillatory patterns across diverse cognitive and emotional states. Examining alpha and theta power, frontal asymmetry, coherence and sensorimotor rhythms, paper attempts through Resilience Recovery Time, elevated alpha power under resting conditions, refined sensorimotor rhythms, efficient alpha/theta ratios and asymmetrical frontal engagement to decode stable traits and adaptive strategies that differentiate individuals that distinguish exceptional individuals from typical functioning. Findings suggest elevated alpha reflect ability to sustain focused yet flexible mental states, crucial for innovation and performance under complexity. Neurofeedback enabled conscious control over these patterns, reinforcing hypothesis that ability to modulate one's brain state is critical to sustained performance. Paper offers future directions in deciphering predictive value of EEG microstates and spectral power in resilience contexts. Paper points at future research in exploring how QEEG markers can guide real-time, adaptive interventions for understanding and enhancing peak performance.

The paper convincingly illustrates the correlation between specific brainwave patterns and states of peak performance, offering a promising direction for optimizing individual capabilities in diverse fields such as sports, art, and academics. By leveraging qEEG technology, high performers have the opportunity to gain insights into their brain function and apply neurofeedback training for enhancement in performance. However, while the evidence presented is compelling and suggests significant benefits from understanding neurophysiological signatures, more comprehensive longitudinal studies would solidify the causative links between brainwave modulation and performance improvements. Future research should focus not only on elite performers but also on a broader population to generalize findings and maximize the potential for performance improvement across various activities. Furthermore, ethical considerations regarding the use of neuro-technological tools must be addressed, ensuring they are employed responsibly and equitably.

The paper underscores the impact of brainwave patterns on psychological states and their relevance in achieving a mental state conducive to peak performance. By understanding these dynamics, individuals can better manage focus and anxiety, which are critical in high-pressure scenarios. By employing qEEG technology, the paper acknowledges the advancements in neuro-technology that allow researchers and practitioners to gain deeper insights into brain activities. This technological lens illustrates how modern tools can transform the way performance psychology is approached. The reliance on scientific studies to support claims is a strong aspect of the paper. The empirical data lend credibility to the assertion that identifying and training specific brainwave patterns can lead to significant improvements in various performance arenas. The call for future research opens avenues for exploration. It emphasizes the evolving nature of understanding brain function and performance, encouraging ongoing inquiry into how neurophysiological signatures can be integrated into training regimes for diverse populations.

In summary, the exploration of neuro-physiological signatures of peak performance through a quantitative qEEG lens sheds light on the intricate relationship between brain activity and optimal functioning. The insights gained from identifying specific brainwave patterns not only enhance our understanding of performance dynamics but also offer practical strategies for individuals looking to reach their full potential. The advocacy for further research indicates a commitment to refining these findings into actionable coaching and therapeutic methods, ultimately enriching the lives of individuals across various disciplines. By capitalizing on technological advancements in neuroscience, we are poised to transform training practices, paving the way for significant enhancements in performance outcomes.

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