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THE BRAIN FUNCTION ANALYSIS (BFA) FRAMEWORK: A NEUROPHYSIOLOGICAL VALIDATION OF INTEGRATED QUANTITATIVE EEG (QEEG) METRICS

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ABSTRACT
Quantitative Electroencephalography (QEEG) is a powerful tool in neuroscience, but a gap exists between raw data and fragmented outcomes. The Brain Function Analysis (BFA) framework aims to bridge this gap through 11 key metrics of neurophysiological integration into a single and cohesive report. The objective of this paper is to provide a scientific validation in the BFA framework by reviewing 11 neurophysiological principles metrics. A literature review was conducted to examine the scientific basis for each metric. The review confirms all 11 metrics supported by decades of peer-reviewed research in neuroscience and psychophysiology. The paper demonstrates that these metrics serve as reliable indicators of cognitive processes and emotional states. In addition, the BFA Framework is scientifically credible and validates QEEG metrics into a holistic and interpretable profile. BFA Framework could become a valuable practitioner's tool for data development and personalised interventions to support cognitive function and emotional well-being.

Keywords: Quantitative Electroencephalography (QEEG), Brain Function Analysis (BFA), Applied Neuroscience, Neurofeedback, Frontal Alpha Asymmetry, Cognitive Function

1. INTRODUCTION

1.1 The Emergence of Applied Neuroscience

Neuroscience offers practical tools in cognitive function and mental assessment (Cucino et al., 2022). Society seeks objective brain health reports rather than subjective ones (Zhang et al., 2024). Nowadays, data utilisation and technology assists people's well-being and performance improvement (Zakrzewski, 2022). Quantitative Electroencephalography (QEEG) can assess brain electrical activity to interpret deeper brain function (Onagawa et al., 2023). QEEG can convert raw brainwave data into standardized metrics to identify attention, stress, and emotional regulation patterns. Subsequently, QEEG is useful in creating personalized training programs for performance improvement (Mirifar et al., 2017).

The BFA framework's principles and applications align with the cutting-edge and interdisciplinary field of neuroscience to explore the mental and behaviours (Cucino et al., 2022). The BFA framework also serves as a powerful instrument for leadership development, performance optimization, and entrepreneurship research by providing data on stress, attention, cognitive load, and emotional regulation (Cucino et al., 2022). However, a significant challenge in the applied neuroscience field is the fragmentation of data. Most QEEG assessments provide isolated metrics and leave practitioners or individuals with a data points collection rather than an integrated and holistic brain function understanding.

One challenge that effective neurofeedback and analysis systems aim to solve is bridging the gap between raw data and actionable insights in practical applications (Cucino et al., 2022; Mirifar et al., 2017). The BFA framework developed to address this gap by synthesizing multiple validated neurophysiological markers into a single and cohesive report. This paper provides scientific validation for these 11 metrics and demonstrates a comprehensive and reliable framework to assess neurocognitive and emotional states.

The BFA framework developed by the Korea Research Institute of Brain Science (Koreabsi) and Brainscience Academy Sdn Bhd (Brainsc) to address this fragmentation through synthesizing various validated neurophysiological markers into a single and comprehensive report. This paper aims to provide a scientific validation for the 11-core metrics of this framework and demonstrate it as a comprehensive and reliable method to assess neurocognitive and emotional states. Overall, this paper outlines the principles of QEEG with deconstructions and validates the 11 BFA metrics by grounding them in established scientific literature, discusses the integrated value in framework and future directions.

1.2 Conceptual Objectives

This paper aims to deconstruct and validate the 11 metrics of the BFA Framework report by grounding them in established neuroscientific principles, thereby integrating knowledge from neuroscience, psychology, and signal processing. The BFA framework serves as a useful map for brain complexity, yet it does not directly measure objective reality because the mind requires deeper inquiry into consciousness (Zakrzewski, 2022).

In addition, this paper outlines QEEG principles to establish understanding on the BFA framework and validate BFA core metric by connecting it to scientific literature. The discussion is based on the BFA Report Framework from Korea Research Institute of Brain Science (Koreabsi) and Brainscience Academy Sdn Bhd (Brainsc). Lastly, this paper will establish the BFA framework as a scientifically valid framework for objective brain function assessment by showing the neurobiological foundation of its metrics.

2. METHODOLOGY: DATA ACQUISITION AND PROCESSING

The BFA framework data is acquired through a standardized QEEG protocol and is consistent with established research practices to evaluate cognitive performance and neurofeedback intervention effectiveness (Zhang et al., 2024; Onagawa et al., 2023).

2.1 BFA Framework Data Acquisition and Processing

The primary data collection instrument is using a non-invasive device headband called "BrainSc EEG headband" by placing two electrodes on the forehead at positions Fp1-Fp2 and clipping a pair of reference electrode to both earlobe. The headband position follows the international 10-20 system, and portable EEG devices in naturalistic settings (Zhang et al., 2024).

Participants are seated comfortably in a quiet environment to minimize environmental interference, and standard protocol captures brainwave patterns during two distinct conditions. First is 40-second baseline recording with eyes open and followed by a 40-second recording with eyes closed before switch back to eyes open for 40-seconds. This dual-condition assessment allows the evaluation of brain wave reactivity and reflects the brain's ability to shift between internal and external attentional states (Mirifar et al., 2017).

2.2 Signal Processing and Data Analysis

Data is captured using a non-invasive BrainSc EEG headband connected to the cloud-supported BrainScience Neurofeedback program that utilises Artificial Intelligence (AI)-driven techniques for real-time analysis. Captured EEG raw data then undergoes a rigorous pre-processing pipeline to ensure quality and validity of raw data through application of band-pass filter (eliminate extraneous noise), artefact detection algorithms and muscle tension (EMG). Artefacts removal is a critical step to achieve reliable QEEG results (Mirifar et al., 2017).

Fast Fourier Transform (FFT) algorithm will process clean data and this spectral analysis deconstructs the signal into constituent frequency bands (Delta, Theta, Alpha and Beta) and calculates the band power spectral density respectively. This quantitative data forms the foundation for 11 metrics presented in the final BFA Report and the entire process is aligned with standard methodologies in neuroscience research (Cucino et al., 202; Onagawa et al., 2023).

2.3 Literature Review Methodology for Framework Validation

To validate the 11 metrics of the BFA framework, a targeted literature review was conducted and focused on identifying peer-reviewed studies that form the scientific basis for each neurophysiological principle used in the framework. Key scientific databases, including PubMed, Scopus, and Google Scholar, were searched for relevant literature. Search terms were specific to each BFA metric but were not limited to "Quantitative EEG," "Frontal Alpha Asymmetry," "Individual Alpha Frequency," "Theta/SMR ratio AND attention," "EEG coherence," "neurofeedback," and "alpha blocking."

The inclusion criteria for selecting literature were: (1) peer-reviewed articles, including original research, meta-analyses, and systematic reviews; (2) studies involving human subjects; (3) research focusing on the neurophysiological correlates of cognitive and emotional states relevant to the BFA metrics. No specific date range was applied to capture both foundational and contemporary research. Studies focusing exclusively on severe clinical pathologies without relevance to general cognitive or emotional function were excluded. This process ensured that each BFA metric was substantiated by established and credible scientific evidence.

3. BRAIN FUNCTION ANALYSIS FRAMEWORK

Neuroplasticity is the brain's ability to reorganize its structure from experience (Kang et al., 2023). The BFA framework is a brain function assessment that uses QEEG to process the brain's electrical activity. The BFA framework details cognitive and psychological states to transform complex data into clear 11 metrics. The framework assesses cortical arousal, stress responses, and hemispheric balance to give a complete view of a person's neurocognitive landscape. An approach rooted in neuroplasticity is understanding one's brain activity patterns and allowing the BFA framework to operate in the core principle of targeted training and optimize function. The BFA Framework maps self-regulation, measures progress and proposes a model for understanding brain function through validated indicators.

3.1 The Brainwave Graph

The Brainwave Graph (BG) offers a ratio-amplitude of brainwaves and patterns in different brain characteristics through spectral analysis forms (Zhang et al., 2024). This technique utilizes Fast Fourier Transform (FFT) algorithm and deconstructs the raw EEG signal into their respective frequencies (Sho'ouri et al., 2019; Zhang et al., 2024). A power spectrum measures the energy at each frequency and allows neuroscientists to identify dominant brain rhythms and states of consciousness (Zakrzewski, 2022). The BFA makes the Brainwave Graph a functional biomarker where high alpha power indicates relaxation and high beta power signifies active thought (Mirifar et al., 2017). BFA objectively measures the balance between these states by quantifying power within each band."

Delta (δ, 0.5-4 Hz) is the slowest brainwave during deep sleep and important for restoration

(Cheron et al., 2016). Appearing Delta during waking states represents cortical slowing or fatigue (Lehrer & Woolfolk, 2021; Zhang et al., 2024). Theta (θ, 4-8 Hz) waves characterize light sleep and deep internal focus (Mirifar et al., 2017), but elevated waking theta indicates attention deficit hyperactivity disorder (ADHD) (Lubar & Shouse, 1976).

Alpha (α, 8-12 Hz) is the dominant rhythm in a healthy individual at rest with eyes closed (Mirifar et al., 2017) and represents calm alertness. The brain uses alpha activity to actively inhibit irrelevant areas and allocates resources to essential processing (Klimesch et al., 2007). Sensorimotor Rhythm (SMR, 12-15 Hz) is a frequency band over the sensorimotor cortex and associated with focused attention (Gruzelier, 2014). SMR through neurofeedback improves motor precision (Ros et al., 2009; Cheng et al., 2015). Beta (β, 13-30 Hz) waves indicate active brain characteristic and High-frequency beta waves are associated with anxiety and mental stress (Mirifar et al., 2017; Cucino et al., 2022). The primary frequency bands used within the BFA framework are summarized in Table 1.

Table 1. The BFA Framework Frequency Band

Band Name	Frequency Range (Hz)	Primary Associated States	BFA Relevance	Key Citations
Delta (δ)	0.5-4 Hz	Deep sleep, memory consolidation. In wakefulness: cognitive impairment, learning disabilities.	Foundational marker for assessing states of deep rest and identifying potential markers of cognitive dysfunction.	(Mirifar et al., 2017); (Christoffersen & Schachtman, 2016)
Theta (θ)	4-8 Hz	Drowsiness, intuition, memory encoding and retrieval. Frontal theta increases with cognitive load.	Core component of the Memory Index and Cognitive Stress metric. Elevated resting theta is relevant to the Brain Arousal metric.	(Mirifar et al., 2017); (Guleken et al., 2020).
Alpha (α)	8-12 Hz	Dominant rhythm in a relaxed, wakeful state (eyes closed). Associated with calmness and self-awareness.	Central to Brain Speed (Peak Alpha Frequency) and Emotional Bias (Frontal Asymmetry). Alpha reactivity is key to the Feedback Ability metric.	(Mirifar et al., 2017); (Cucino et al., 2022)

Band Name	Frequency Range (Hz)	Primary Associated States	BFA Relevance	Key Citations
SMR	12-15 Hz	Relaxed attentiveness, focused attention, reduced impulsivity, and sensorimotor inhibition.	A key component of the Attention Index, reflecting the capacity for sustained, calm focus.	(Mirifar et al., 2017); (Onagawa et al., 2023)
Beta (β)	16-30 Hz	Low-Beta (16–20 Hz): Active problem-solving, focus. High-Beta (21–30 Hz): Tension, anxiety, stress, negative rumination.	Low-beta is a key component of the Concentration Index. High beta is the primary marker for the Mental Stress metric.	(Mirifar et al., 2017); (Cucino et al., 2022)

Source: Author own's work

3.2 Brain Activity Rhythm

The BFA report evaluates the "Brain Activity Rhythm (BAR)" to show the brain's processing speed. The BAR metric assesses the dominant brainwave frequency and compares it to normative data by neuroscientific concept application through Individual Alpha Frequency (IAF), also known as peak alpha frequency (Pérez-Elvira et al., 2021). The BFA report evaluates the rhythm's dominant frequency, which is the specific frequency with the highest relative strength or power. Frequency measures the number of brainwave cycles per second in Hertz (Hz). Relative strength reflects the signal's amplitude and how many neurons groups fire in synchrony (Cucino et al., 2022). Then, BFA compares this dominant frequency to a standard for normative benchmark. In addition, this comparison uses a specific standard of age-group.

Brain maturation research shows the dominant frequency is not static across the lifespan (Mirifar et al., 2017; Zakrzewski, 2022). The peak alpha frequency then continues to increase linearly and reaches its fastest point around age 16, then beginning to slowly decline in later adulthood. This well-documented developmental trajectory makes a single standard for all ages is scientifically invalid (Zhang et al., 2024). The BFA's use of an age-standard ratio is therefore a methodologically sound approach that accounts for these maturational changes. This comparison of an individual's IAF dominant frequency to an age-appropriate standard can provide a validated biomarker for their intrinsic cognitive tempo and processing efficiency (Klimesch, 1996; Klimesch, 1999).

Research shows the frequency at which an individual's alpha rhythm peaks is a stable characteristic (Klimesch, 1999). This IAF correlates with information processing speed and a higher IAF suggests faster reaction times while a lower IAF suggests cognitive slowing (Klimesch, 1996; Onagawa et al., 2023). A lower processing speed than the standard indicates slower processing and a higher speed than standard suggests faster processing. An optimal speed aligns with the standard. The BFA provides a validated biomarker for cognitive tempo.

3.3 Changes in EEG During Open-Close Eyes (Brainwave Reactivity)

The BFA report assesses the change in brainwave amplitude during eyes-open and eyes-closed conditions. A stable brainwave during the closed-eye state indicates good brain function and the change upon opening the eyes is a key part of this assessment.

This BFA metric is validated by "alpha blocking" or "alpha reactivity" brainwave reactivity (Christoffersen & Schachtman, 2016). In a healthy individual, a state of relaxed wakefulness with eyes closed is characterized by dominant, high-amplitude alpha waves, particularly over the occipital lobe, which reflects the disengagement of the visual system (Adrian & Matthews, 1934; Mirifar et al., 2017; Zhang et al., 2024). Visual information engages the cortex when the eyes open, and this shift in attention suppresses the alpha rhythm. This state of alertness and active thinking is instead dominated by faster beta waves (Walter, 1938; Mirifar et al., 2017; Zhang et al., 2024). A positive figure in the report indicates a good transition, while a negative figure suggests a non-optimal transition. This may affect sleep quality or show inflammation. This test assesses the brain's ability to effectively manage sensory information, as alpha activity is associated with the top-down control of attention to suppress information that is irrelevant to a task (Afrash et al., 2023). A rapid suppression of alpha waves indicates the brain can efficiently switch from internal to external processing, whereas a weak response may suggest a non-optimal state for shifting attention.

3.4 Changes in Alpha Wave Power

The BFA framework uses alpha wave dynamics in two ways. First is the overall power of the alpha band that indicates relaxation and second is "Emotional Orientation" that compares brainwave intensity between the left and right hemispheres.

The link between alpha power and relaxation is well-established and increasing of alpha activity is a correlate of a relaxed and wakeful state (Mirifar et al., 2017). A low amplitude of alpha power indicates fatigue, but a high amplitude suggests restricted awareness. It is the target rhythm in meditation and relaxation training (Kamiya, 1979).

3.5 Brain Arousal (Theta/SMR Ratio)

The BFA framework defines "Brain Arousal" through the ratio of theta power to sensorimotor rhythm (SMR) power. This metric shows the brain's arousal state and high Theta/SMR ratio means cortical under-arousal (hypoarousal). A ratio lower than the standard suggests hyperarousal.

The Theta/SMR ratio is a validated marker for brain arousal. Elevated theta activity is a marker of a low-arousal state (Gruzelier, 2014). The BFA framework's metric compares the ratio to an age-standardized norm, which extensive neurodevelopmental research scientifically supports.

SMR activity is associated with calm, focused readiness (Cheng et al., 2015). This ratio is a cornerstone of neurofeedback protocols for ADHD (Micoulaud-Franchi et al., 2014). ADHD individuals show excessive theta and deficient SMR activity because it is a cortical under-arousal signature (Lubar & Shouse, 1976). Neurofeedback training trains ADHD individuals to decrease theta and increase SMR power to shift their brain state toward focus (Guleken et al., 2020). The success of these protocols validates the BFA's use of the Theta/SMR ratio. Arousal is a complex state and this ratio provides an operationalized measure of one of its neural correlates (Turabee et al., 2025).

3.6 Feedback Ability

The BFA framework includes "Feedback Ability" to demonstrate how the brain effectively regulates brainwaves when needed. Neurofeedback training provides scientific validation for this component and applies operant conditioning principles to brain function (Mirifar et al., 2017). The process measures brainwave activity and presents it back to the person in real-time (Sho'ouri, 2021). This "Feedback Ability" measures success in the learning process by assessing the brain's capacity for neuroplastic self-regulation and change from training (Ghaziri et al., 2013; Kang et al., 2023). A high feedback ability indicates a strong capacity for neuroplastic change.

3.7 Left and Right Brain Balance

The BFA report provides a visualization of "Left and Right Brain Balance" to show the symmetry and synchronization of brain activity, together with a balanced state is presented as optimal.

Interhemispheric coherence and amplitude symmetry validate this BFA metric with efficient communication between functional cognitive hemispheres (Cucino et al., 2022). It is important to move beyond "left-brain and right-brain" myths with integration and not dominance (Zagha & McCormick, 2014). Coherence (synchrony) measures the phase consistency between EEG signals and found that high coherence indicates strong functional connectivity (Bhattacharya & Petsche, 2005) and value should be greater than 50% for optimal function.

Amplitude Symmetry refers to the relative power of brainwaves in corresponding regions and imbalances suggest inefficient processing (Trujillo et al., 2017). A symmetry value exceeding 80% is considered optimal and research on elite archers found they achieved peak performance with a specific hemispheric asymmetry (Landers et al., 1991). This shows optimal function is not always about perfect symmetry but to achieve the appropriate and task-specific balance.

3.8 Physical and Mental Stress

The BFA report quantifies stress with scores for "Physical Stress" and "Mental Stress." Physical Stress indicates bodily tension, and Mental Stress shows mental distraction and anxiety. EEG research validates these metrics by identifying a "stress signature." High mental stress is associated with increased power in the high beta frequency band (Mirifar et al., 2017), and this high-beta activity reflects cortical hyper-arousal (Lehrer & Woolfolk, 2021), whereas a lower score for Mental Stress indicates less distraction.

The BFA framework links Physical Stress to the Delta wave, and a lower score indicates a greater ability to perform under stress, which this distinction requires critical viewing. The profound mind-body connection connects mental and physical stress as aspects of a single response system (Zakrzewski, 2022). Studies on Generalized Anxiety Disorder (GAD) found a pattern of low SMR and high beta wave amplitudes (Lehrer & Woolfolk, 2021).

3.9 Behavioural Orientation & Emotional Orientation

The BFA framework shows a person's tendencies using "Emotional Orientation" and "Behavioural Orientation." "Emotional Orientation" uses the Frontal Alpha Asymmetry (FAA) model, which links activity in the left front of the brain to wanting to approach things and activity in the right front of the brain to wanting to withdraw from things (Cucino et al., 2022). "Behavioural Orientation" is validated by examining the Alpha/Low Beta ratio.

This ratio shows how the brain mainly operates and BFA sees an imbalance in this ratio as a sign of behavioural tendencies. Strong left-brain activity means a positive outlook, while strong right-brain activity indicates caution. A balanced ratio suggests a general style by using frequency ratios is a good analytical choice because it normalizes individual brain data. This creates a useful marker for how neurocognitive systems work together.

The BFA's "Emotional Orientation" metric applies the concept of Frontal Alpha Asymmetry (FAA). This research focuses on the balance of alpha power between the left and right frontal lobes. An asymmetry in alpha power reflects an asymmetry in cortical activation (Cucino et al., 2022).

Research has linked this asymmetry to two motivational directions. First, greater right frontal activity is associated with approach motivation, extroverted individuals, and this pattern is linked to positive states (Peterson et al., 2008). Second, Greater left frontal activity is associated with withdrawal motivation, introverted individuals, and this pattern is linked to negative states like depression (Hammond, 2005).

This marker reflects embodied emotional tendencies because the mind and body are not separate. Strong communication between them is a sign of health and disconnection is a sign of disease (Zakrzewski, 2022). The FAA is a window into this mind-body state and reflecting an individual's orientation toward or away from the world.

3.10 Synthesis and Conclusion: A Holistic and Scientifically Grounded Framework

3.10.1 Integration of the 11 Components

This paper deconstructed and validated the 11 metrics of the BFA framework in neuroscientific principles. The value of the BFA lies in the holistic integration of the entire profile because all components work together to create a detailed picture of an individual's neurophysiological state. The BFA provides data to make these distinctions, as summarized in Table 2.

Table 2. The BFA Framework Components Framework

BFA Component	Validating Neurophysiological Principle/Concept	Key Supporting Citations
Brainwave Graph	Spectral Analysis (FFT) of EEG Frequency Bands	(Mirifar et al., 2017); (Zhang et al., 2024)
Changes in EEG (Open-Close Eyes)	Alertness and Active Thinking	(Walter, 1938); (Mirifar et al., 2017); (Zhang et al., 2024)
Changes in Alpha Wave Power	Alpha Power as a Correlate of Relaxation	(Mirifar et al., 2017)
Brain Activity Rhythm	Individual Alpha Frequency (IAF) as a Trait Marker	(Klimesch, 1999)
Feedback Ability	Operant Conditioning of Brainwaves / Neuroplasticity	(Mirifar et al., 2017); (Kang et al., 2023)

BFA Component	Validating Neurophysiological Principle/Concept	Key Supporting Citations
Brain Arousal	Theta/SMR (or Theta/Beta) Ratio for Cortical Arousal	(Guleken et al., 2020); (Micoulaud-Franchi et al., 2014)
Left and Right Brain Balance	Interhemispheric Coherence and Amplitude Symmetry	(Landers et al., 1991); (Cucino et al., 2022)
Physical Stress	Somatic Correlates of Delta States	(Zhang et al., 2024)
Mental Stress	High-Beta Power as a Marker for Anxiety/Hyper-arousal	(Mirifar et al., 2017); (Lehrer & Woolfolk, 2021)
Behavioural Orientation	Alpha/Beta Ratio as an Index of Internal vs. External Focus	(Zhang et al., 2024)
Emotional Orientation	Frontal Alpha Asymmetry (FAA) and Motivational Direction	(Cucino et al., 2022); (Davidson, 2004)

Source: Author own’s work

4. DISCUSSION

The BFA framework provides a multi-dimensional view of brain function and addresses the limits of single biomarkers. A common QEEG finding (high Theta-to-Beta ratio) existing in individuals with attention difficulties suggests inattention. However, cortical under-arousal or anxiety-driven distraction can cause this pattern. This difference is important for effective intervention. Sustaining focus is difficult when a brain cortex exhibits reduced activation (Sterman, 2000). Excessive theta waves compared to beta waves in a QEEG suggest a person is distracted like anxiety because it can distract someone by using up their mental resources. This constant state of alertness often comes with too much high-beta activity (Mirifar et al., 2017).

The BFA framework gives distinct metrics for Brain Arousal (Theta/SMR Ratio) and Mental Stress (High Beta) allowing practitioners to differentiate between opposing neurophysiological states. Slow brain speed and high Theta/SMR Ratio suggest cognitive sluggishness but fast brain speed with high mental stress indicates a racing mind. Furthermore, the Brain Balance predictor assesses communication efficiency between brain regions and poor coherence can explain a lack of focus regardless of arousal levels. This integrated assessment creates a detailed neurological picture and intervention for under-arousal with slow brain speed would differ greatly from a strategy for anxiety with negative emotional bias. This multi-metric approach prevents misdiagnosis and helps create effective personalized support.

5. CONCLUSION

5.1 From Assessment to Intervention

This paper established a scientific foundation for the BFA's core metrics and became transparent science tools. The BFA utilizes the brain's neuroplasticity to encourage lasting change and serve a data-driven roadmap for personalized interventions (Pindi et al., 2022). The personalized BFA moves beyond one-size-fits-all protocols to identify specific training targets.

5.2 Future Directions

Neuroscience and BFA Framework evolving and future development should focus on key areas. First is large-scale expansion and diverse databases for data accuracy. Second, integrate BFA Framework metrics with other advanced technologies and other physiological sensors (Lopez-Bernal et al., 2022). The BFA framework's commitment to scientific transparency and ethical application can lead to an understanding of the human brain. A pragmatic approach requires viewing diverse mind models as provisional and subject to revision as understanding grows (Zakrzewski, 2022).

The BFA framework translates neurophysiological data into a clear and actionable profile of brain function. 11 scientifically validated QEEG metrics integrations gives a complete understanding of a person's cognitive and emotional state. This approach is not diagnostic but serves as a map to guide personalized interventions to improve well-being and optimize performance. Frameworks like the BFA will become more central to data-driven approaches in mental health education and human performance.

5.3 Limitation

While the BFA framework provides a robust, integrated assessment, it is important to acknowledge its limitations and outline directions for future development. First, the framework relies on a two-channel EEG headband acquiring data from the Fp1 and Fp2 site. This hardware still has limitations even though the configuration is highly accessible and excellent to capture frontal lobe activity like emotional regulation and executive function. It possesses lower spatial resolution than full-cap QEEG systems and cannot assess coherence or activity in posterior brain regions. Future affirmation could explore the additional sensor integration to comprehensive topographical analysis.

Second, brainwave patterns are state-dependent and can be influenced by transient contextual factors such as recent sleep quality, caffeine intake, or immediate emotional stress even though QEEG offers objective data. Practitioners using the BFA framework should consider these variables when interpreting results and ideally conduct assessments under standardized and calm conditions to ensure reliability.

Finally, it must be reaffirmed that the BFA framework is an assessment to guide personalized interventions and is not a diagnostic tool. It provides a detailed profile of an individual's neurocognitive functioning but should not be used to diagnose clinical disorders like ADHD or anxiety. Future research should focus on longitudinal studies to track the efficacy of BFA-guided neurofeedback protocols and further refine the normative databases across more diverse demographics to enhance the precision and applicability of the framework.

6.0 CONFLICT OF INTEREST STATEMENT

The authors are affiliated with the Korea Research Institute of Brain Science (Koreabsi) and Brainscience Academy Sdn Bhd (Brainsc), the institutions that developed and utilised the BFA framework discussed in this paper.

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