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THE EEG-BASED LEARNING ABILITY AND MENTAL HEALTH ASSESSMENT (MLA) FRAMEWORK: A CONCEPTUAL MODEL INTEGRATING NEUROPHYSIOLOGICAL, EMOTIONAL, AND COGNITIVE INDICATORS

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ABSTRACT

Understanding the neurophysiological basis of learning ability and mental health is becoming increasingly important in neuroscience, education, and clinical psychology. However, many current assessments mainly rely on behavioural or psychometric measures that do not account for internal neural mechanisms. The EEG-Based Learning Ability and Mental Health Assessment (MLA) Framework addresses this gap by combining twelve neuro-cognitive-emotional indicators derived from real-time EEG data. These indicators reflect how effectively a person can stay focused, maintain optimal alertness, regulate emotions, cope with stress, manage fatigue, balance left- and right-brain activity, and remain physiologically prepared to perform. This provides a comprehensive, human-centred view of brain function that illustrates how the brain operates in real-world learning and performance contexts. This conceptual paper examines the theoretical principles of each indicator and consolidates findings from cognitive neuroscience, affective neuroscience, psychophysiology, and EEG research to support the framework. The MLA Framework views brain activity as an interconnected system, offering a clearer understanding of learning readiness and mental state. It is designed for use in education, early screening, mental health assessment, and personalised neurofeedback, while also recognising the ongoing need for further empirical validation and the establishment of robust normative data.

Keywords: EEG-based assessment; learning ability; mental health; brainwave indicators; neurophysiology; educational neuroscience; school-based screening; neurofeedback

1. INTRODUCTION

1.1 Neuroscience Foundations for EEG-Based Assessment

Progress in EEG research has confirmed that typical EEG rhythmic activities have specific physiological sources and functional roles, aiding their understanding in research and practical self-regulation applications (Sterman, 1996). EEG-based assessment methods have evolved over numerous decades, beginning with Berger's pioneering recordings of human brain activity (Lubar, 1991). Since then, a considerable amount of research has demonstrated that different EEG frequency bands, including delta, theta, alpha, beta, and gamma, are closely linked to key cognitive functions such as attention, working memory, information processing, and cognitive integration (Klimesch, 1996, 1999; Klimesch et al., 2006; Başar, 2013). Modern neuroscience highlights a network-focused view of brain activity, in which dynamic interactions among large-scale systems drive cognition, emotion, and self-control. This perspective is outlined by Bassett & Sporns (2017) and exemplified by Menon’s (2011) triple-network model of brain organisation. Pessoa's idea of the "entangled brain" highlights how perception, cognition, and emotion are deeply interconnected (Pessoa, 2022). From this viewpoint, EEG patterns linked to learning and mental health are seen as indicators of coordinated activity across brain networks, rather than as isolated signals from individual regions.

Alpha and theta oscillations have been consistently linked to learning, memory, and attentional control, and they show characteristic changes during states of fatigue, reduced alertness, and cognitive impairment (Klimesch, 1996, 1999). In parallel, slow-wave activity and faster rhythms, particularly beta and sensorimotor rhythm (SMR), are closely associated with arousal regulation, motor control, behavioural inhibition, and sustained attention. These relationships form the empirical basis of many traditional neurofeedback protocols (Lubar & Shouse, 1976; Landers et al., 1991; Sterman, 1996). Overall, these results show that EEG offers a multidimensional signal that can detect learning readiness, maintain attentional stability, and identify susceptibility to anxiety, depression, and chronic stress.

1.2 Rationale for an Integrated Learning and Mental Health Model

The increasing challenges worldwide and locally highlight the importance of adopting a more holistic approach to education and mental health. The World Health Organization recognises depression and anxiety as major contributors to the global disease burden, noting that these conditions often develop during childhood and adolescence and remain widely under-detected and undertreated worldwide (World Health Organization, 2017, 2023). In Malaysia, official government data show an increasing number of people registered with mental disabilities across the country, indicating a heightened awareness of mental health concerns (Daily Express, 2024). National surveillance programmes, such as the National Health and Morbidity Survey, continue to track population health trends, including mental health status (Institute for Public Health, 2023). At the tertiary education level, research among Malaysian university students consistently reports high levels of depression, anxiety, and stress symptoms, highlighting the ongoing concern of mental health within this group (Hassan et al., 2022; Husin et al., 2022).

Learning difficulties often occur alongside emotional and behavioural challenges, including increased anxiety and lower self-confidence, highlighting the strong link between academic achievement and mental health (Sahoo et al., 2015; Ihbour et al., 2021; Adi et al., 2024; Teoh, 2010). Despite ongoing efforts to promote inclusive and evidence-based education, Malaysian schools mainly depend on behavioural observations and psychometric screening for identification (Ministry of Education Malaysia, 2013, 2022). These approaches can be helpful but might miss underlying issues such as chronic stress, sleep problems, or emotional dysregulation, especially in students who are quiet, compliant, or socially withdrawn.

Although EEG and neurofeedback research have grown, most applications remain limited to clinical or laboratory settings. Reviews indicate that EEG and neurofeedback could provide benefits for conditions like ADHD, anxiety, and depression. However, they also point out significant differences in training protocols, outcome measures, and practitioner expertise levels (Arns et al., 2017; Markiewicz, 2017; Micoulaud-Franchi et al., 2014; Sitaram et al., 2017). As a result, a knowledge gap persists between neuroscience and the development of large-scale cum practical assessment tools designed to evaluate learning ability and mental health in educational settings.

1.3 Conceptual Objectives of the MLA Framework

The EEG-based Learning Ability and Mental Health Assessment (MLA) Framework addresses this gap by introducing twelve integrated indicators that reflect neurophysiological, cognitive, emotional, and physiological functioning. Grounded in educational neuroscience perspectives that emphasise the dynamic interplay between brain networks, emotion, and environmental context (Immordino-Yang et al., 2019; Holmes, 2019), the framework is designed around three core objectives. It initially simplifies complex EEG data into simple indicators like relaxation, attention, arousal, and sleep, making it easier for non-experts to interpret (Wlodek, 2018; Rossignoli-Palomeque et al., 2018). Second, it integrates learning and mental health indicators into a single profile, drawing attention to the shared neural networks that support both cognitive and emotional processes (Bassett & Sporns, 2017; Menon, 2011; Pessoa, 2022). Third, it provides a theory-based foundation for validation and for EEG-guided interventions, including neurofeedback, that are well suited to personalised support and school-based implementation (Sherlin et al., 2011; Arns et al., 2009; Sitaram et al., 2017).

1.4 Significance for Education, Mental Health, and Policy

By bringing together EEG with educational and public health perspectives, neuroscience-driven frameworks offer practical ways to support attention, motivation, and social-emotional well-being through more effective classroom practices and community-based initiatives (Immordino-Yang et al., 2019; Holmes, 2019; Bevilacqua et al., 2019). This approach supports both global and Malaysian priorities that focus on early detection, community-oriented care, and the integration of mental health services within school settings (World Health Organization, 2017, 2023; Tengku Mohd et al., 2023; Ministry of Health Malaysia, 2024; Bernama, 2024). The framework structures EEG data into clear, understandable, and trackable indicators over time, helping practitioners establish practical neurofeedback assessment goals and confidently associate neural patterns with meaningful educational and mental health results (Arns et al., 2017; Markiewicz, 2017; Russo, 2021; Dias et al., 2024).

2. METHODOLOGY: Literature Review Methodology for Framework Validation

2.1 Literature Selection Strategy

The EEG-Based Learning Ability and Mental Health Assessment (MLA) Framework was created through a systematic, concept-driven review of literature using curated sources and targeted searches of major scientific databases. Because of the framework's conceptual nature, inclusion criteria were limited to methodologically rigorous studies directly related to one or more of the twelve MLA indicators. Eligible studies employed EEG or QEEG as their main measurement tools and focused on constructs such as attention, concentration, relaxation, anxiety, depression, stress reactivity, sleep quality, hemispheric balance, arousal, and physiological markers linked to fatigue or inflammation. To maintain relevance for school-aged populations, studies with human participants spanning from childhood to adulthood were included, ensuring developmental applicability across different age groups.

Priority was placed on peer-reviewed journal articles, scholarly books, and high-quality reports published in English that offered detailed methodology to facilitate clear interpretation of EEG indices concerning functional outcomes. Systematic reviews and meta-analyses of EEG-neurofeedback and EEG- or BCI-based interventions were prioritised, as they synthesise evidence relevant to executive functions, attentional processes, and socio-emotional regulation (Viviani & Vallesi, 2021; Micoulaud-Franchi et al., 2014; Doulou et al., 2025). Studies were excluded if EEG findings were described only in technical terms without connection to cognition, emotion, or behaviour, or if they were restricted to conference abstracts, single-case reports, or solely based on non-EEG imaging methods. However, important works from network, affective, and educational neuroscience were kept despite missing EEG data, as they offer crucial theoretical background on brain–emotion-learning interactions (Bassett & Sporns, 2017; Menon, 2011; Pessoa, 2022; Immordino-Yang et al., 2019; Holmes, 2019).

2.2 Framework Validation Approach

Consistent with recent reviews in the EEG–neurofeedback literature, the validity of the MLA Framework was established through a structured narrative synthesis rather than a quantitative meta-analysis (Viviani & Vallesi, 2021; Micoulaud-Franchi et al., 2014; Doulou et al., 2025). Each indicator was first operationally defined to clearly distinguish between related yet conceptually distinct domains, such as Attention versus Brain Arousal and Anxiety Tendency versus Stress Resistance. The literature was then systematically analysed to identify EEG features associated with these constructs, including frequency-band power, topographical distributions, hemispheric asymmetries, and dynamic changes observed under resting and task-based conditions.

Evidence connecting alpha and theta oscillations with attention, concentration, memory, and learning readiness informed the fundamental learning indicators of the framework (Klimesch, 1996, 1999; Klimesch et al., 2006; Başar, 2013). Indicators of anxiety, depression, and stress resilience are based on well-known links with high-beta activity, frontal EEG asymmetry, and stress-related EEG patterns, which are standard markers used in assessment and neurofeedback (Sterman, 2000; Markiewicz, 2017; Micoulaud-Franchi et al., 2014).

2.3 Evidence Synthesis

The evidence synthesis aimed to refine constructs and improve interpretability, drawing on principles from mixed-methods and conceptual reviews (Creswell & Creswell, 2017; Guetterman, 2015). Different types of studies, including experimental, observational, review-based, and theoretical work, were integrated using thematic coding to identify shared patterns in EEG-behaviour relationships, methodological quality, and the clarity of functional interpretations. Consistent links between alpha power, frontal midline theta, and attentional control supported the Attention and Concentration indicators. Meanwhile, consistent evidence on high-beta activity and asymmetry supports treating Anxiety and Depression Tendency as distinct yet related factors. The Sleep Quality, Brain Voltage, and Inflammation Tendency indicators were influenced by sleep-related EEG changes, including low-voltage or slowed patterns associated with fatigue and inflammation. This synthesis verified that all MLA indicators are grounded in empirical evidence, consistent with theoretical frameworks, and appropriate for use in educational, clinical, and preventive contexts.

3. THE EEG-BASED LEARNING ABILITY AND MENTAL HEALTH ASSESSMENT (MLA) FRAMEWORK

The EEG-Based Learning Ability and Mental Health Assessment (MLA) Framework offers an integrated model that connects brain activity with learning capacity, emotional well-being, stress control, sleep, and overall brain-body health. It translates established EEG features into twelve clear and interpretable indicators that collectively reflect learning readiness and cognitive functioning. Evidence consistently shows that EEG oscillations in the alpha, theta, and beta bands are closely associated with cognitive efficiency, emotional regulation, and adaptive functioning, supporting the use of EEG as a practical and informative assessment tool (Klimesch, 1996, 1999; Hammond, 2011; Soufineyestani et al., 2020).

3.1 Conceptual Overview

The MLA framework combines neuroelectrical, cognitive, emotional, and physiological signals into a unified assessment system. Alpha, theta, and beta EEG rhythms consistently reflect key functional brain states related to memory, attention, arousal, and processing efficiency (Klimesch, 1996, 1999; Enriquez-Geppert et al., 2017). Research in educational EEG further suggests that learning outcomes are shaped by levels of neural engagement and synchronisation during instruction, highlighting the importance of neural readiness and brain-state regulation rather than isolated individual skills (Bevilacqua et al., 2019; Wlodek, 2018).

The framework also acknowledges that brain function is part of wider physiological and psychosocial contexts. Population data indicate that sleep issues, stress, and emotional struggles are common in youth and frequently occur alongside learning difficulties (Institute for Public Health, 2019, 2023). Emerging evidence connects immune, metabolic, and nutritional factors to EEG activity and mood, supporting the inclusion of physiological indicators like brain activation and inflammation in comprehensive brain-health assessments (Kang et al., 2023; Tsalamandris et al., 2023).

3.2 Description of the Twelve MLA Indicators

Indicator 1. 3D Brainwave Graph

The 3D Brainwave Graph displays delta-beta activity across scalp regions with multi-channel EEG, allowing quick detection of patterns at the regional, hemispheric, and network levels (Soufineyestani et al., 2020).

Indicator 2. Relaxation

Relaxation indicates the brain's capacity to decrease arousal and stay calm and receptive. It mainly depends on the stability of alpha rhythms, which are linked to relaxed wakefulness, filtering sensory input, and effective attention-memory functions (Klimesch, 1996; Klimesch et al., 2006).

Indicator 3. Attention

Attention involves maintaining and choosing focus, typically measured via sensorimotor rhythm (SMR) activity in the brain's central regions. Neurofeedback and clinical EEG research associate consistent SMR control with better attention, whereas higher low-frequency activity and EEG instability correlate with attentional lapses (Lubar, 1991; Sherlin et al., 2011; Nazari et al., 2011; Helps et al., 2010; Slater et al., 2022).

Indicator 4. Concentration
Concentration indicates the capacity to maintain effort over time. Proper levels of low beta activity promote sustained concentration, whereas high fast beta activity can be linked to anxiety and mental fatigue (Hammond, 2004; Escolano et al., 2011; Wang & Hsieh, 2013). Differentiating concentration from attention helps distinguish temporary orienting issues from persistent cognitive exhaustion.

Indicator 5. Anxiety Tendency
Anxiety Tendency reflects EEG patterns associated with hyperarousal and anticipatory stress, including increased fast beta activity and frontal asymmetry. EEG-based intervention reviews recognise anxiety-related EEG patterns as biologically meaningful correlates that can disrupt learning and social engagement (Hammond, 2004; Mennella et al., 2017; Micoulaud-Franchi et al., 2015, 2021).

Indicator 6. Depression Tendency
Depression Tendency indicates EEG patterns related to low motivation and withdrawal, such as atypical frontal alpha asymmetry and lower alpha power. Although not diagnostic by themselves, these EEG patterns are associated with depressive symptoms and reduced engagement, underscoring the need for supportive follow-up (Markiewicz, 2017; Micoulaud-Franchi et al., 2015; Melnikov, 2021).

Indicator 7. Stress Resistance
Stress Resistance reflects the brain's ability to maintain organised activity under pressure, as shown by delta rhythms. EEG self-regulation studies demonstrate that neural stability supports performance and emotional balance during increased demands (Sterman, 1996; Sherlin et al., 2011; Faller et al., 2019).

Indicator 8. Left-right Balance
Left-right hemispheric balance in EEG frequency bands indicates differences in attention, emotional style, and perceptual processing (Nazari et al., 2011; Barbot & Carrasco, 2018).

Indicator 9. Brain Arousal
Brain Arousal indicates overall cortical activation, involving interactions among theta, and SMR activities. Systems neuroscience evidence shows that peak performance depends on adaptable arousal control rather than fixed trait levels (Sterman, 1996; Sherlin et al., 2011; Zagha & McCormick, 2014).

Indicator 10. Sleep Quality

Sleep Quality reflects restorative brain activity, characterised by slow-wave patterns and a lack of ongoing high-frequency disruptions. Poor sleep correlates with higher stress and emotional instability, which can impair learning capacity (Institute for Public Health, 2019; Roy et al., 2020).

Indicator 11. Brain Voltage

Brain Voltage reflects the amplitude and energetic strength of EEG signals, associated with cognitive efficiency, resilience, and memory performance. Organised EEG power facilitates effective information processing, while consistently low voltage can point to fatigue or overload (Sterman, 1996; Gordon et al., 2020; Nawaz et al., 2023).

Indicator 12. Inflammation Tendency

Inflammation Tendency is a conceptual indicator reflecting EEG instability that may be linked to systemic inflammatory or metabolic influences. Interdisciplinary evidence connects stress, immune activity, and nutrition to neural function and cognition, supporting a comprehensive interpretation of this indicator (Kang et al., 2023; Tsalamandris et al., 2023).

Table 1 summarises the twelve MLA indicators, outlining their EEG basis, core conceptual meaning, and relevance to learning ability and mental health within the overall assessment framework.

Table 1. Summary of the Twelve MLA Indicators: EEG Basis, Conceptual Meaning, and Relevance

Indicator	**EEG basis (key features)**	**Conceptual meaning**	**Relevance for learning / mental health**
1. 3D Brainwave Graph	Topographical distribution of delta, theta, alpha, beta power across scalp regions	Global organisation of cortical activity; patterns of overactivation, underactivation, hemispheric dominance, and network imbalance	Provides baseline “map” of brain function; helps contextualise all other indicators and identify broad risk or strength patterns
2. Relaxation	Alpha (≈8-12 Hz) stability, coherence, and appropriate expression at rest	Capacity to down-regulate arousal, release tension, and maintain a calm but alert internal state	Supports receptive learning, memory encoding, flexible thinking, and recovery after stress; low relaxation linked to chronic hypervigilance
3. Attention	SMR engagement during task; fronto-parietal activation dynamics	Orienting to relevant stimuli and selectively maintaining focus while inhibiting distractions	Crucial for classroom engagement, following instructions, and consistent task performance; weak attention linked to distractibility and inconsistent work quality
4. Concentration	low-beta (≈16-20 Hz)	Sustained focus, mental effort, and task persistence over time	Underpins the ability to complete assignments, maintain working memory load, and avoid cognitive drifting; weak concentration associated with rapid fatigue and incomplete tasks

Indicator	EEG basis (key features)	Conceptual meaning	Relevance for learning / mental health
5. Anxiety Tendency	High-beta dominance; right-frontal and related asymmetry patterns; instability in fast activity	Propensity toward cognitive worry, hyperarousal, anticipatory stress, and heightened threat monitoring	Elevated anxiety interferes with clear thinking, attention, and social ease; increases risk for somatic complaints and exam-related stress
6. Depression Tendency	Frontal alpha asymmetry; globally reduced alpha power; low, non-reactive activity patterns	Tendency toward low motivation, withdrawal-oriented affect, and reduced executive drive	Helps explain disengagement and "switched-off" presentation despite intact ability; associated with low initiative and reduced enjoyment of learning
7. Stress Resistance	Ability to limit excessive delta surges; delta changes under prolonged demand	Capacity to preserve neural organisation and functional stability during cognitive or emotional challenge	High stress resistance supports performance under pressure and smoother recovery; low stress resistance linked to rapid overwhelm, emotional outbursts, or shutdown in demanding situations
8. Left-Right Balance	Relative brainwave patterns across homologous left-right regions	Degree of hemispheric symmetry or asymmetry in processing style and emotional tone	Imbalances may be associated with emotional dysregulation or uneven verbal-nonverbal skills; balanced profiles support coordinated cognitive and affective functioning
9. Brain Arousal	Global configuration of theta and SMR; shifts in fast/slow ratios	Overall activation level of the central nervous system, from hypoaroused to hyperaroused states	Low arousal linked to fatigue, slow processing, and under-engagement; high arousal linked to restlessness, impulsivity, and anxiety; optimal arousal supports alert, flexible learning
10. Sleep Quality	Change in brainwave between eyes-closed and eyes-open	Effectiveness of restorative sleep and sleep-wake regulation	Poor sleep quality undermines daytime attention, emotional stability, and learning capacity; good sleep supports resilience, mood, and consolidation of new information
11. Brain Voltage	Overall alpha amplitude across key bands; peak-frequency and power characteristics	Neural "energy" level and cortical effectiveness in generating and sustaining activity	Low voltage suggests reduced stamina, underarousal, or metabolic strain; high but organised voltage suggests strong neural engagement, whereas very high, unstable voltage may reflect tension or sensory overload
12. Inflammation Tendency	Abnormal in regulation of brainwave between eyes-closed and eyes-open and instability patterns consistent	Indirect marker of potential brain-body stress related to inflammation, immune/microvascular load, or metabolic factors	Elevated tendency linked conceptually to fatigue, mood disturbance, and slower cognitive processing; lower tendency suggests more favourable

Indicator	EEG basis (key features)	Conceptual meaning	Relevance for learning / mental health
	with systemic physiological burden		physiological background for learning and mental health

Source: Author own's work

3.3 Inter-Indicator Relationships and Framework Model

The MLA indicators function as an interconnected system instead of standalone scores. Emotional indicators are strongly related to Brain Arousal and Sleep Quality, while cognitive indicators rely on Relaxation, arousal balance, and hemispheric coordination (Hammond, 2004; Micoulaud-Franchi et al., 2014; Nazari et al., 2011; Slater et al., 2022). Brain voltage and inflammation act as physiological moderators influencing how cognitive and emotional resources are mobilised (Peterson et al., 2008; Tsalamandris et al., 2023).

Within the MLA Framework Model, these indicators are arranged in concentric layers, placing Attention and Concentration at the centre. Surrounding this core are indicators related to neural state regulation, emotional resilience, and the broader physiological context that supports learning and mental health. This layered approach reflects educational neuroscience views, emphasising that learning arises from the interaction between brain state, emotion, bodily regulation, and real-world context (Immordino-Yang et al., 2019; Bevilacqua et al., 2019). Table 2 shows how the twelve MLA indicators cluster into four functional domains within the overall framework.

Table 2. **Functional Grouping of MLA Indicators into Global, Cognitive, Emotional, and Physiological Domains**

Domain	MLA indicators included	Primary role in the framework	Typical questions this domain helps to answer
Global brain organisation	3D Brainwave Graph, Left-Right Balance	Describes overall organisation of cortical activity and hemispheric patterning, including over/underactivation and asymmetry.	"How is this learner's brain generally organised? Are there broad patterns of imbalance that shape all other indicators?"
Cognitive readiness and learning efficiency	Attention, Concentration, Brain Arousal, Brain Voltage	Captures core neurocognitive conditions for learning: ability to focus, sustain effort, maintain optimal arousal, and generate sufficient neural energy.	"Is the brain ready to learn? Can this learner focus, stay with tasks, and process information efficiently?"
Emotional functioning and stress response	Relaxation, Anxiety Tendency, Depression Tendency, Stress Resistance	Reflects emotional tone, vulnerability to anxiety and low mood, and capacity to stay regulated under challenge.	"Is emotional state helping or hindering learning? How does this learner cope with pressure, mistakes, or change?"
Brain-body / physiological health background	Sleep Quality, Inflammation Tendency	Represents systemic factors (restorative sleep, physiological burden) that influence energy, mood, and cognitive stamina.	"Are underlying brain-body factors such as sleep and physiological stress limiting attention, mood, or stamina?"

Source: Author own's work

4. DISCUSSION

The EEG-Based Learning Ability and Mental Health Assessment (MLA) Framework was created to respond to two emerging trends: the increasing use of EEG and neurofeedback technologies, and the growing occurrence of learning difficulties, mental health issues, and developmental disabilities in children and adolescents. Many learners face interconnected cognitive, emotional, and behavioural challenges that are often overlooked or identified late. This highlights the importance of assessment methods that promote earlier, more compassionate, and integrated understanding. Within this context, the MLA framework converts complex EEG signals into twelve understandable indicators that aid in educational and mental health decisions.

4.1 Conceptual Contribution of the MLA Framework

Conceptually, MLA considers EEG as part of a biopsychosocial approach to learning and mental health rather than merely a limited assessment instrument. Recent neuroplasticity research indicates that brain structure and function can be altered throughout a person's life, influenced by experience, training, and environmental factors (Doidge, 2007; Kolb & Gibb, 2014). The twelve indicators represent essential areas highlighted in current research, including attention and executive function, emotional regulation and stress, sleep and fatigue, hemispheric balance, and overall brain-body health. By integrating these into a single profile, MLA fosters an understanding of learning and mental health through network-based methods instead of focusing only on symptoms or deficits.

The framework is further supported by studies demonstrating that EEG rhythms reflect daily cognitive and emotional conditions and can be modified through training. Systematic reviews indicate that EEG-based neurofeedback and cognitive training may improve executive functions, including working memory. However, these findings are constrained by small sample sizes and differences in methodology (Viviani & Vallesi, 2021; Matsuzaki et al., 2023). Narrative reviews indicate that neurofeedback and biofeedback are used for various conditions including ADHD, anxiety, chronic pain, and performance enhancement, reinforcing the idea that EEG-based indicators serve as changeable functional goals.

4.2 Implications for Education and Early Identification

From an educational standpoint, MLA defines “learning readiness” using neurophysiological concepts. Studies indicate that individuals with neurodevelopmental disorders often exhibit inconsistent executive function profiles, affecting their participation in classroom activities and the support they require. Research using classroom EEG demonstrates that increased neural synchronisation between teachers and students correlates with higher engagement and improved learning outcomes, highlighting the importance of real-time brain activity during lessons. In this context, indicators such as Attention, Concentration, Brain Arousal, and Brain Voltage can help identify learners who possess adequate cognitive capacity but struggle to mobilise or maintain neural resources during learning. MLA is not intended to replace pedagogical assessments or psychometric tests. It instead provides a cognitive view that improves current techniques and can steer more targeted teaching approaches.

4.3 Integrating MLA with Neurofeedback and Digital Interventions

The MLA framework offers a transparent rationale for designing interventions. Reviews of neurofeedback indicate growing benefits for ADHD, anxiety, and performance enhancement, yet they also reveal notable differences in protocols and outcomes (Markiewicz, 2017; Matsuzaki et al., 2023; Viviani & Vallesi, 2021). By explicitly linking EEG features with functional indicators, MLA facilitates a more coherent order of interventions, like focusing on arousal and sleep prior to intensive attention training.

4.4 Mental Health, Brain-Body Health, and Holistic Care

By including indicators such as anxiety, depression, stress, sleep, neural energy, and inflammation, the MLA framework reflects growing recognition that learning and mental health are closely shaped by ongoing interactions between the brain and the body. Highlighting these factors promotes integrated support strategies that go beyond classroom instruction and align with holistic biofeedback and neurofeedback approaches.

4.5 Methodological and Implementation Considerations

Methodological challenges remain. Reviews regularly highlight significant differences in study quality, practitioner training, and long-term follow-up in EEG-based interventions (Viviani & Vallesi, 2021; Rossignoli-Palomeque et al., 2018). Therefore, as a conceptual framework, MLA needs empirical validation across various cultures, age groups, and service environments. Its use should be integrated within multidisciplinary assessment processes to minimise over-interpretation and support responsible, equitable implementation.

5. CONCLUSION

5.1 Summary

The EEG-Based Learning Ability and Mental Health Assessment (MLA) Framework serves as a conceptual connection between neuroscience and applied educational and clinical practices. The framework translates EEG activity into twelve clear and interpretable indicators, offering a broad view of brain organisation, learning potential, emotional regulation, stress resilience, sleep, and overall brain-body health. This approach aligns with evidence showing that brain function remains adaptable across the lifespan and can be shaped through experience and training (Doidge, 2007; Kolb & Gibb, 2014). It also addresses global and national evidence showing considerable mental health issues among children and teenagers, including in Malaysia (Institute for Public Health, 2019; World Health Organization, 2017, 2023). Conceptually, MLA considers learning and mental health to be closely linked neurophysiological processes. It is designed to complement, not replace, behavioural and psychometric assessments (Adi et al., 2024; Lehrer & Woolfolk, 2021).

5.2 Limitations

MLA functions as a theoretical framework and has not yet been empirically validated for diagnostic uses. Different brain-training and EEG-based study methods complicate the process of linking simple EEG features to more complex concepts (Arns et al., 2009; Matsuzaki et al., 2023; Rossignoli-Palomeque et al., 2018). Implementation remains limited by practical factors such as cost, training needs, and fair access (Soufineyestani et al., 2020; Adi et al., 2024).

5.3 Future Directions

Future research should prioritise empirical validation, longitudinal investigation, and the development of normative data, alongside the integration of relevant physiological and lifestyle measures. At the same time, such work should be guided by strong ethical standards and a clear focus on user-centred implementation.

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