THE INFLUENCE OF INTERVAL STRUCTURE ON NEUROPHYSIOLOGICAL AND PERCEPTUAL RESPONSES TO HIGH-INTENSITY INTERVAL TRAINING (HIIT): A COMPARISON OF FIXED VS. INDIVIDUALIZED BOUTS

by

ARSALAN GHOFRANI

A dissertation submitted to the
Department of Computer Science
in conformity with the requirements for
the degree of Master of Science

Bishop's University
Canada
May 2026

Abstract

This thesis investigated how two high-intensity interval training (HIIT) protocols—Psychological HIIT with fixed bout durations and Physiological HIIT with individualized bout durations based on each participant's time limit at maximal aerobic speed (MAS)—influence EEG oscillations and affect responses in untrained female participants. The primary research question examined whether differences in interval structure led to distinct neural recovery patterns and post-exercise affect responses. Three objectives were addressed: (1) to assess the effects of each HIIT protocol on enjoyment, perceived exertion, affective valence, and mood; (2) to compare post-exercise changes in EEG theta, alpha, and beta power, including frontal asymmetry, between protocols; and (3) to examine correlations between EEG changes and perceptual and affect measures. Twenty untrained female participants completed both HIIT protocols in a within-subjects crossover design. EEG activity (theta, alpha, and beta power, as well as frontal asymmetry) was recorded before and after exercise during seated rest and a cognitive task (Tetris). Affect measures included enjoyment (Physical Activity Enjoyment Scale; PACES), perceived exertion (RPE), affective valence (Feeling Scale), and mood state (Profile of Mood States; POMS). EEG signals were preprocessed using ICA for artifact removal and analyzed using Welch's power spectral density method.

Results showed that Psychological HIIT was associated with higher post-exercise enjoyment ($p = 0.009$) and lower anger scores ($p = 0.040$) compared with Physiological HIIT, despite similar perceived exertion during exercise. EEG analyses revealed greater post-exercise increases in theta, alpha, and beta power following Psychological HIIT, particularly over frontal and central regions. During the post-exercise Tetris task, a distinct theta-band frontal asymmetry pattern emerged: Physiological HIIT was associated with a right-dominant shift, whereas Psychological HIIT showed a left-dominant shift. Exploratory correlation analyses further indicated inconsistent and protocol-specific associations between EEG changes and affect outcomes.

Overall, these findings indicate that HIIT interval structure influences both EEG oscillatory activity and affect responses. Differences between Psychological and Physiological HIIT were observed in post-exercise neural and perceptual outcomes, indicating that interval structure is associated with exercise-related responses.

Acknowledgments

I would like to sincerely thank my supervisors, Dr. Russell Butler and Dr. Danilo Fernandes da Silva, for their continuous support, expert guidance, and thoughtful feedback throughout every stage of this research. Their mentorship not only shaped the direction of this project but also played a key role in my academic and personal growth. I am deeply grateful for their encouragement and belief in my work.

Special thanks to Sara Bonyadian for her collaborative teamwork and technical contributions throughout the project.

List of Abbreviations

EEG	Electroencephalography
HIIT	High-Intensity Interval Training
HR	Heart Rate
HRV	Heart Rate Variability
PACES	Physical Activity Enjoyment Scale
RPE	Rating of Perceived Exertion
POMS	Profile of Mood States
FS	Feeling Scale
TMD	Total Mood Disturbance
MAS	Maximal Aerobic Speed
$t_{\mathbf{lim}}$	Time Limit at Maximal Aerobic Speed
VO_2max	Maximal Oxygen Consumption
MICT	Moderate-Intensity Continuous Training
FFT	Fast Fourier Transform
PSD	Power Spectral Density
ICA	Independent Component Analysis
EMG	Electromyography
EOG	Electrooculography
FA	Frontal Asymmetry
FDR	False Discovery Rate
SD	Standard Deviation
ΔPower	Post-minus-Pre EEG Power Difference
GIQ	General Information Questionnaire
PAR-Q+	Physical Activity Readiness Questionnaire Plus
PS	Psychological HIIT Condition
PH	Physiological HIIT Condition
MNE	Python package for MEG/EEG analysis
SciPy	Python library for scientific computing
Statsmodels	Python library for statistical modeling
Matplotlib	Python library for data visualization
Welch's Method	Averaging-based power spectral density estimation technique

Contents

List of Tables

List of Figures

Chapter 1

Introduction

High-Intensity Interval Training (HIIT) is a form of interval training that alternates between short bouts of high-intensity exercise and periods of lower-intensity rest. In several cases, high-intensity exercise is prescribed at intensities associated with an important predictor of performance: maximal oxygen consumption (VO_2max) [12]. These intensities are often referred to as Maximal Aerobic Speed (MAS) since VO_2max is an indicator of aerobic fitness. These high-intensity intervals at MAS typically last from a few seconds to a few minutes and are followed by active (easy exercise) or passive (no exercise) recovery periods [44]. The health benefits of HIIT are significant, as it has been shown to improve cardiovascular health, reduce fat mass, and increase fitness (e.g., VO_2max) [85]. HIIT's time efficiency is a key advantage when compared to traditional exercise modalities (e.g., moderate-intensity continuous training). While continuous exercise typically requires longer periods of sustained effort at light-to-moderate intensity, HIIT can achieve similar benefits in much shorter session durations (e.g., 20 minutes versus 60 minutes), making it particularly appealing for individuals with busy schedules [35, 99].

A specific design of HIIT sessions became popular in the exercise science literature due to its positive psychological responses. In this thesis, we refer to this type of HIIT as *Psychological HIIT*. The bout duration of Psychological HIIT is usually one minute, and the work-to-rest ratio is commonly 1:1, meaning one minute of effort followed by one minute of rest. The number of bouts depends on the plan for the total session duration, but it tends to be no more than 15 bouts (approximately 30 minutes total duration) [94, 98]. Research has shown that running bouts of approximately one minute appear to be more enjoyable when compared to longer bout durations [98].

Another alternative to prescribing HIIT at MAS, comprehensively studied during the 1990s and 2000s, is the one proposed by Billat et al. [11]. In this thesis, we refer to this type of HIIT as *Physiological HIIT*. Similar to Psychological HIIT, the work-to-rest ratio of Physiological HIIT is commonly 1:1. However, the duration of the high-intensity exercise bout is determined by another variable, called time limit

(t_{lim}) at MAS. Besides determining MAS, prescribing this type of HIIT requires participants to complete the t_{lim} at MAS test, which consists of measuring how long an individual can exercise at their MAS. The use of t_{lim} at MAS is justified by its greater individualization for bout duration, as it presents a large inter-individual coefficient of variation (25–34%, varying approximately from 2 to 12 minutes, with an average of about 6 minutes) even when MAS is homogeneous [11]. This large variation is explained by inter-individual differences in anaerobic capacity, which physiologically reflects the ability to sustain intensities near the occurrence of VO_2max [68]. Even though this HIIT approach is associated with performance-related benefits due to its enhanced physiological foundation, it is not well known whether this HIIT design results in more positive affect responses given its greater individualization.

Affect responses, especially exercise enjoyment, are considered key components in explaining exercise adherence [34]. This is particularly relevant for untrained populations that use running to increase physical activity levels, which has increased among female individuals [60]. Research has shown mixed results regarding affect experienced during HIIT, with some studies reporting negative affect [39, 96], whereas others have noted positive affect [55, 59, 66]. These discrepancies may be explained by neurophysiological factors and the interaction between brain activation, feelings, and emotions.

The relationship between brain activation and emotion can be conceptualized through electroencephalographic (EEG) asymmetry in frontal brain regions, which has been linked to affect responses [80]. Asymmetry in these regions reflects predispositions to emotional reactions, with right frontal activation associated with negative emotions and left frontal activation linked to positive emotions [90]. Resting EEG asymmetry serves as a biological marker for affect responses, predicting emotional responses to stimuli [97]. Heller's framework [52, 53] proposes that affect responses can be evaluated along two dimensions: valence (pleasure vs. displeasure) and arousal (high vs. low). According to this framework, valence is assessed through EEG activity in anterior brain regions, while arousal is linked to activity in the right parietal region, reflecting physiological and autonomic responses to emotional stimuli.

In the context of exercise, EEG activity changes across frequency bands, including delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), and gamma (>30 Hz), reflect shifts in cognitive and emotional states. Acute exercise has been shown to increase cortical activity, enhancing cognitive functions such as attention and working memory, and altering EEG frequencies [45]. Moreover, Gramkow et al. [45] highlighted that changes in theta, alpha, and beta oscillations are commonly reported when assessing the effects of HIIT.

Acute exercise is not only a peripheral physiological stressor; it may also be accompanied by short-term changes in brain activity that can be examined with EEG. High-intensity exercise, in particular, is likely to engage processes such as attentional control, interoceptive monitoring, and fatigue-related regulation, which have been associated with fronto-central networks and oscillatory dynamics. For instance, theta-band activity has been linked to cognitive control and performance monitoring [21], processes that may be especially relevant during HIIT where participants repeatedly regulate effort across bouts and recovery. In parallel, prior HIIT research suggests that protocol characteristics (e.g., interval duration and work–rest structure) can influence perceptual and psychological responses such as perceived exertion and enjoyment [6, 57, 58, 74]. Taken together, this literature motivates examining whether different HIIT prescriptions (fixed-bout "Psychological" vs. individualized-bout "Physiological") are associated with differences in post-exercise EEG measures (e.g., theta/alpha/beta power changes) that may reflect variation in neural responses to intermittent physiological demands.

EEG is also relevant to the study of mood and affect because several theoretical and empirical frameworks relate frontal activity patterns to emotional and motivational tendencies. Frontal EEG asymmetry—often operationalized as relative left–right differences in alpha-band activity—has been used to study approach-versus withdrawal-related motivational states and traits [27]. This perspective is useful in exercise research because acute exercise is frequently associated with changes in affective state (e.g., shifts in mood dimensions such as tension, vigor, or overall mood disturbance) [14, 31, 103], and affective responses are thought to contribute to adherence and engagement, including in demanding modalities such as HIIT [6, 57]. Moreover, exercise can be treated as a state manipulation that may alter frontal activity relative to baseline (i.e., from "activity" at rest to post-exercise "activation"), consistent with recommendations to interpret asymmetry measures as potentially reflecting both trait-like and state-sensitive processes depending on context. In the exercise literature, a systematic review has summarized evidence linking prefrontal asymmetry to psychological responses to exercise [91], and related work has examined whether regional brain activation measures are associated with affective responsivity to acute exercise [79]. Collectively, these findings provide a rationale for testing whether post-HIIT EEG changes covary with enjoyment, perceived exertion, and mood outcomes in the present thesis.

The relationship between EEG measures and affect responses has been largely examined in different types of exercise (e.g., light and moderate continuous exercise), but not in HIIT. Exercise and affect research has consistently demonstrated that exercise elicits a "feel-better" effect, including decreased state anxiety, anger, and tension, and increased perceived vigor and pleasure [101]. Investigations have examined how EEG alterations, specifically in the frontal areas, relate to these affect responses. For example, aerobic continuous exercise research has demonstrated that brain activation changes, such as increased alpha and theta activity [61, 69]. These investigations, however, have largely looked at moderate-intensity aerobic exercise or less intense forms of it. Conversely, the extent to which HIIT affects neurophysiological responses and the relationship these responses have with affect, specifically enjoyment and emotional engagement, is less understood. For instance, whereas brain activation changes due to exercise have been demonstrated in exercises such as running and tracking [69], how HIIT specifically influences these neurophysiological responses and how they relate to affective states like enjoyment or exertion is yet to be investigated. This constitutes a significant literature gap in that the HIIT protocols, including psychological and physiological HIITs, due to their distinct intermittent nature (i.e., number of bouts and bout duration), may induce a different pattern of brain activation and emotional responses that are not accounted for in research on other types of exercise.

From a computer science perspective, the current study utilizes advanced computational approaches to process and analyze large, multimodal datasets. Data acquisition is the first step, where EEG signals are collected alongside perceptual variables (rating of perceived exertion [RPE], enjoyment, pleasure/displeasure feelings, and mood state). Next, the EEG signals are subjected to signal processing methods such as the Fast Fourier Transform (FFT) and Welch's method to estimate power spectral densities and extract relevant spectral features. Then, the data are pre-processed using Independent Component Analysis (ICA) to remove noise and artifacts (i.e., eye movements and muscle activity), ensuring signal integrity and reliability for subsequent analysis. These methods showcase the practical application of computer science tools in neuroscience, highlighting their role in managing, processing, and analyzing complex datasets. In this study, we further explore the potential to apply these tools in the context of exercise science to better understand differences in perceptual affect markers.

Main Objective The main objective of this thesis is to determine whether two HIIT prescriptions—a fixed-bout protocol (Psychological HIIT) and an individualized-bout protocol (Physiological HIIT)—are associated with different post-exercise EEG responses and affective outcomes (enjoyment, perceived exertion, affective valence, and mood) in untrained female participants, and to evaluate whether EEG changes are related to these perceptual and mood measures.

Specific Objectives and Work Steps

Step 1 (Data preparation). EEG and questionnaire data are organized by participant, protocol (Psychological vs. Physiological), and timepoint (pre vs. post). Standardized preprocessing is applied to obtain artifact-reduced EEG signals suitable for analysis.

Step 2 (EEG feature extraction). For each protocol and timepoint, spectral features are extracted by computing band-limited power in theta, alpha, and beta ranges, and deriving pre-to-post change scores.

Step 3 (Protocol comparison). Post-exercise EEG power changes are compared between Psychological and Physiological HIIT to test whether the two prescriptions are associated with different neurophysiological responses.

Step 4 (Affective and perceptual outcomes). Enjoyment, perceived exertion, affective valence, and mood outcomes are quantified and compared between protocols to characterize differences in subjective response profiles.

Step 5 (Brain–behavior relationships). Associations between EEG changes (theta/alpha/beta power) and affective/perceptual measures are examined to identify potential neurophysiological correlates of enjoyment, exertion, and mood responses.

Contribution This thesis contributes empirical evidence on whether fixed-bout versus individualized-bout HIIT prescriptions are associated with different post-exercise EEG oscillatory responses and affective outcomes in an untrained female sample. Methodologically, the work provides a reproducible workflow for extracting band-power features (theta, alpha, beta) from pre/post exercise EEG recordings and relating these neurophysiological indices to enjoyment, perceived exertion, affective valence, and mood measures. By combining standardized EEG preprocessing with feature extraction and brain–behavior analyses, the study offers a structured approach for investigating neurophysiological correlates of affect during HIIT.

Thesis Structure This thesis is organized as follows: Chapter 1 introduces HIIT, distinguishes the Psychological and Physiological prescriptions, and motivates the study by linking affective responses with EEG-based markers of brain activity. Chapter 2 reviews the relevant literature on HIIT protocol design, affect and perceptual responses to exercise, and EEG-based findings (including oscillatory activity and frontal asymmetry) in the context of exercise and mood. Chapter 3 details the methodology, including participant recruitment, the four-visit experimental protocol, EEG and perceptual measurements, and the preprocessing and statistical analysis pipeline. Chapter 4 presents the results, first describing perceptual and mood outcomes and then reporting post-exercise EEG changes (theta, alpha, and beta power, including frontal asymmetry) and exploratory EEG–behavior associations. Chapter 5 discusses the findings in relation to prior work, outlines limitations and strengths, and highlights implications for understanding affective and neurophysiological responses to different HIIT prescriptions. Finally, Chapter 6 concludes the thesis by summarizing the main contributions and proposing directions for future research.

Chapter 2

Literature Review

This chapter positions the thesis within two complementary research areas: sports science and computer science. From the sports science perspective, we summarize how HIIT can be prescribed (including fixed-bout and individualized approaches) and how interval structure relates to perceptual and affective responses that are relevant to adherence. From the computer science perspective, we summarize the signal-processing and analytical methods required to extract reproducible EEG features from noisy recordings (e.g., spectral estimation using FFT/Welch methods and artifact correction using ICA), and we motivate why these methods are necessary for studying exercise-related brain dynamics. Together, these sections establish the conceptual and methodological foundation for comparing Psychological versus Physiological HIIT using integrated behavioral and EEG outcomes.

2.1 Overview of High-Intensity Interval Training (HIIT)

In 2007, HIIT was defined by Gibala et al. as a type of exercise involving alternating bouts of very high-intensity exercise, usually at 80–100% of maximal effort, with low-intensity active recovery or passive rest [42, 43]. In many cases, the high-intensity work is prescribed at intensities associated with VO_2max, a key predictor of aerobic performance, and expressed as maximal aerobic speed (MAS) [12]. Later, in 2014, Gibala et al. specified that these intervals at MAS generally last from a few seconds to a few minutes and are interspersed with either active (light exercise) or passive (rest) recovery periods [44].

Interval training was first described in cardiac rehabilitation research in 1972, where patients cycled at high work rates for 60 seconds with 30 seconds of rest between periods, allowing them to exercise for at least double the duration compared with continuous cycling [92]. By 1979, high-intensity exercise was recommended to improve cardiovascular function in patients with recent myocardial infarctions [77]. These findings were important, and evidence from both the general population and athletic cohorts has demonstrated that higher exercise intensity augments training adaptations, including VO_2max, anaerobic threshold, stroke volume, and performance [99]. One of the major advantages of HIIT is its time efficiency, as it can provide similar or superior health benefits compared to continuous training in a shorter duration, addressing common barriers such as lack of time and motivation [99]. Compared with moderate-intensity continuous training (MICT), HIIT can achieve equal or greater improvements in VO_2max, stroke volume, and overall cardiovascular fitness in less total exercise time [99]. Furthermore, for individuals with long-term health conditions, brief bouts of high-intensity exercise may feel easier on breathing than sustained continuous exercise without breaks [9]. Collectively, evidence accumulated over the past several decades has established HIIT as a time-efficient and effective approach for both clinical and public health applications.

The design of a HIIT protocol, particularly the length of work intervals, can significantly influence training adaptations. Franch et al. [38] showed that prolonged intense running and longer intervals improved running economy and time to exhaustion more than shorter intervals, even though each session was designed to induce exhaustion in approximately 20 minutes. However, differences in running velocity, work-to-rest ratios, and accumulated distance between protocols likely contributed to observed physiological differences, as blood and plasma lactate concentrations are sensitive to work rate and exercise duration [7, 22, 23, 83]. When these variables are controlled, it suggests that different HIIT formats may rely on different energy systems and produce distinct adaptations. Beyond physiological outcomes, interval length may also influence perceptual responses such as rating of perceived exertion (RPE), which is linked to buffering capacity and lactate accumulation. Since RPE can affect both exercise adherence and the number of intervals completed in a session, understanding these responses is important for the optimal design of HIIT protocols [84].

Two specific HIIT formats are particularly relevant to the present study. The first, referred to here as *psychological HIIT*, uses short bout durations, typically around one minute, with a 1:1 work-to-rest ratio (e.g., one minute of effort followed by one minute of rest). These sessions usually last no more than 30 minutes and have been reported to be more enjoyable than protocols involving longer work intervals [94, 98]. The second format, referred to here as *physiological HIIT*, prescribes work intervals based on an individual's time limit (t_{lim}) at MAS, determined through a test in which the participant maintains MAS until exhaustion [11]. Although this approach also uses a 1:1 work-to-rest ratio, the individualized bout duration may enhance the precision of the training stimulus. This is particularly relevant because t_{lim} at MAS varies widely between individuals (approximately 2–12 minutes, with an average of about 6 minutes), even when MAS is homogeneous, largely due to differences in anaerobic capacity [68]. While physiological HIIT has a strong physiological rationale for improving performance, its effects on affect responses remain less well understood.

In summary, HIIT is a time-efficient and effective method for improving cardiovascular fitness and performance [42, 43, 99]. However, outcomes depend on protocol design, as factors such as interval length, work-to-rest ratio, and total workload influence both physiological adaptations and perceptual responses [38, 84]. Psychological and physiological HIIT illustrate how variations in interval prescription can alter the balance between enjoyment and physiological optimization, underscoring the importance of examining their relationship with EEG changes and perceptual indicators, including enjoyment, perceived exertion, mood, and heart rate variability (HRV).

2.2 Affect and Perceptual Findings in Exercise and HIIT

Affect responses during exercise, defined as the emotional experiences individuals have while being physically active, are critical for understanding long-term exercise participation [19, 100]. Rhodes and Kates [87] reviewed the literature and noted that many dominant theories of physical activity behavior, such as the Theory of Planned Behavior and Social Cognitive Theory [1, 8], primarily emphasize cognitive processes while underrepresenting affective experiences [33, 64]. Their findings suggest that affective valence, or how pleasant or unpleasant exercise feels, plays a central role in shaping future motivation to exercise [87]. This view aligns with operant conditioning theory, which posits that behaviors associated with positive feelings are more likely to be repeated [49]. Affect responses therefore contribute to broader motivational constructs, such as enjoyment and confidence, and ultimately influence adherence to physical activity. Consequently, how individuals feel during exercise is as important as the physiological effectiveness of the exercise itself, particularly for sustaining long-term healthy behaviors [87].

HIIT has been shown to elicit a distinct pattern of affect responses. Although HIIT and continuous exercise may impose similar cardiovascular demands, participants often report more negative affect during HIIT sessions, including lower scores on the Feeling Scale and higher post-exercise fatigue measured by the Profile of Mood States (POMS) [72]. At the same time, HIIT is associated with higher perceived exertion and arousal, indicating a more intense perceptual experience despite matched physiological intensity [72]. These findings suggest that affect responses during exercise are closely linked to physiological load. As exercise intensity approaches an individual's physical limits, feelings of pleasure tend to decline in a dose-dependent manner [29, 89]. This has led some researchers to caution against prescribing HIIT to untrained or inactive individuals, based on the assumption that high intensity may be perceived as unpleasant [10, 50]. However, more recent evidence challenges this assumption, demonstrating that individuals with lower fitness levels can experience similar or even greater enjoyment during HIIT compared to moderate-intensity continuous exercise [71, 73, 93].

Evidence summarized in a review indicates that how pleasant or unpleasant

Table 2.1: Validated scales for assessing affective and perceptual responses during exercise.

Measure	Scale Format
POMS	Items are rated on a 5-point Likert scale (0 = Not at all to 4 = Extremely). The "Iceberg Profile" reflects an optimal mood state characterized by low negative moods and high vigor.
RPE	Two common versions are used: the Borg 6–20 scale (6 = very, very light to 20 = maximal exertion) and the Borg CR10 scale (0 = nothing at all to 10 = extremely strong [maximal]).
PACES	Items are rated on a 7-point bipolar scale anchored by opposing descriptors (e.g., "I enjoy it" to "I hate it"). Higher scores indicate greater enjoyment.
FS	The scale ranges from +5 (Very good) to −5 (Very bad), with 0 representing a neutral feeling. Positive values indicate pleasure, while negative values indicate displeasure.

exercise feels is closely linked to how hard the body is working, and that very intense exercise often feels unpleasant [32]. However, recent research evidence have found that HIIT, even at very high intensity, can feel just as pleasant or even more pleasant than moderate exercise and is often rated as more enjoyable [71, 73, 93].

2.3 Common Measures of Affect and Perceptual Responses

Several validated tools are used to assess affect and perceptual responses during and after exercise.

The *Profile of Mood States (POMS)* [67, 82] is a questionnaire that measures six mood dimensions: tension, depression, anger, fatigue, confusion, and vigor. It is widely used in sport and exercise psychology to detect changes in mood, with the "iceberg profile" describing a healthy mood state in which negative moods are low and vigor is high [70].

The *Ratings of Perceived Exertion (RPE)* scale [16] is a self-report measure of how hard exercise feels, based on sensations of effort, strain, breathlessness, and fatigue. The Borg CR10 and 6–20 scales are commonly used, with higher scores indicating greater perceived effort [88].

The *Physical Activity Enjoyment Scale (PACES)* [56] is an 18-item questionnaire designed to measure how much a person enjoys a specific physical activity. It is considered a reliable and valid tool for assessing enjoyment, which is strongly linked to long-term exercise adherence.

The *Feeling Scale (FS)* [51] is a single-item measure of affective valence. It captures the basic feeling of pleasure or displeasure during exercise, independent of specific emotions [32, 36].

To provide a concise overview, these measures are summarized in Table 2.1.

2.4 EEG-Based Affect and Cognitive Responses to HIIT

In exercise psychology research, two commonly used methods for measuring psychological responses are self-report instruments and electroencephalography (EEG) [18, 102]. Self-report tools, such as mood scales or questionnaires, allow individuals to reflect on and rate their own emotional or cognitive states [102]. Although subjective measures are essential, they may be prone to bias or influenced by individual differences in perception and interpretation [18, 102]. By contrast, EEG provides a physiological index of brain activation by recording electrical activity across different frequency bands, including delta, theta, alpha, and beta [61, 69]. This method allows researchers to move beyond subjective evaluations, offering a more objective lens into how exercise influences neural dynamics [61].

Numerous studies have used EEG to investigate how brain activity changes during or after exercise, revealing distinct patterns that help explain cognitive and emotional responses [61, 102]. For example, Boutcher and Landers [18] found that participants who completed a 20-minute treadmill run exhibited increased post-exercise alpha activity compared to a reading control condition. Similarly, Petruzzello and Landers [78] reported increased alpha power in the right frontal region following a 30-minute treadmill run, which they interpreted as reduced brain activation. In contrast, Youngstedt et al. [61] observed post-exercise increases in both alpha and beta activity, along with decreased theta power, suggesting enhanced brain activation. More recent research has challenged the assumption of alpha-specific changes. Ciria et al. [24] reported that oscillatory brain activity increased across the entire frequency spectrum during moderate-to-high intensity exercise, with stronger effects at parieto-occipital sites. Similarly, Mierau et al. [69] demonstrated that exhaustive exercise was accompanied by altered EEG activity that coincided with improvements in sensorimotor adaptation, highlighting the role of central nervous system modulation. Complementing these findings, Woo et al. [102] showed that frontal EEG asymmetry following exercise reflected a shift toward approach-related affect states, supporting the link between neural activation patterns and emotional outcomes. Together, these studies illustrate how EEG provides a direct window into brain function during exercise, revealing both global and region-specific changes in neural activity.

Overall, the combination of EEG and self-report measures provides a multidimensional understanding of how exercise influences both psychological and neural processes [61, 102]. While self-report methods offer insight into subjective emotional experience, EEG captures underlying neural activity that may not be consciously accessible [69, 102]. These studies demonstrate that exercise can elicit measurable changes in brain function, including shifts in alpha, beta, and theta activity, as well as frontal asymmetry, depending on factors such as exercise intensity, duration, and individual fitness levels [18, 24, 69, 78]. Consequently, this body of research supports the growing use of EEG in exercise science to complement subjective assessments and to improve understanding of the psychophysiological mechanisms underlying physical activity [24, 102].

2.5 EEG Spectral Analysis Methods: FFT, Welch, and Log Transformations

EEG is widely used in neuroscience and clinical practice because it records brain activity with very high temporal resolution and without the need for invasive procedures [105]. EEG captures small electrical signals generated by synchronized neuronal activity, which are valuable for studying cognitive functions such as memory, attention, language, and emotion, as well as for diagnosing neurological conditions including epilepsy and sleep disorders [105]. Compared with intracranial EEG (iEEG), which is recorded directly within the brain and provides higher signal fidelity, scalp EEG has lower spatial precision but is safer and easier to apply in most experimental and clinical settings [105]. One of the main challenges in EEG analysis is that the recorded signals are often weak and contaminated by noise, making signal processing techniques essential for extracting meaningful information. Over the past two decades, a wide range of analysis methods have been developed, including event-related potential (ERP) analysis and power spectral analysis across frequency bands [2]. These techniques enable researchers to link EEG features with mental and affective states; however, careful selection of processing approaches is critical, as assumptions made during data transformation can significantly influence results [4].

EEG signals recorded at the scalp reflect a mixture of neural sources and non-neural activity (e.g., ocular, muscular, and cardiac artifacts) and therefore require preprocessing and signal processing steps before meaningful comparisons can be made across conditions. In this work, preprocessing included standard steps such as filtering to attenuate slow drifts and high-frequency noise, exclusion of non-EEG channels, and identification/interpolation of noisy channels to improve data quality and comparability across participants. After preprocessing, spectral analysis was used to quantify oscillatory activity in predefined frequency bands of interest. Frequency-domain methods are widely used in EEG because they summarize rhythmic activity as power distributed across frequencies, which can be interpreted as an index of neural state and can be compared across timepoints and experimental conditions. In particular, power spectral density (PSD) estimation provides a principled representation of how signal energy is distributed across frequencies. PSD estimation can be implemented via FFT-based approaches; however, to obtain more stable spectral estimates, Welch's method is often applied by computing periodograms across overlapping, windowed segments of the signal and averaging them. This approach reduces variance and yields smoother PSD estimates that are well suited for estimating band-limited power (e.g., theta, alpha, and beta). Because power values can span a large dynamic range and are often right-skewed, logarithmic (dB) transformations are commonly applied to improve interpretability and support statistical analysis. These concepts motivate the core EEG outcome variables in this thesis, where band-power measures were extracted from pre- and post-exercise recordings and summarized as pre-to-post change scores to quantify protocol-related effects.

A second essential methodological component is artifact correction using Independent Component Analysis (ICA), which is frequently used in EEG research to separate mixed sensor-level signals into statistically independent components that correspond to underlying sources. ICA is based on the assumption that the observed EEG is a linear mixture of temporally independent sources, allowing the data to be decomposed into components with distinct scalp maps and activation time courses. In practice, this decomposition enables identification of artifact-related components, such as eye blinks (typically showing strong frontal projections and slow transient deflections), eye movements, and muscle activity (often characterized by high-frequency content and focal scalp patterns). Removing these components and reconstructing the signal from the remaining components reduces non-neural variance while preserving neural activity of interest. After artifact correction and spectral feature extraction, statistical analysis in this thesis focused on within-subject comparisons between the Psychological and Physiological HIIT protocols. For EEG band power, protocol effects were assessed primarily through comparisons of pre-to-post change (POST − PRE) to control for stable individual differences in baseline power. Normality was assessed using Shapiro–Wilk tests to guide selection of parametric (paired t-test) or non-parametric (Wilcoxon signed-rank) inference, and multiple-comparison control was considered when interpreting electrode-wise results. Finally, exploratory association analyses examined whether EEG changes covaried with perceptual and mood outcomes, using Pearson or Spearman correlations depending on normality. Together, these methods provide a coherent framework for transforming raw EEG and questionnaire data into interpretable indices of oscillatory activity and affective response, and for testing whether interval-structure differences in HIIT are associated with distinct neurophysiological and perceptual outcomes.

2.5.1 Fast Fourier Transform (FFT)

The Fast Fourier Transform (FFT) is one of the most commonly used methods for analyzing EEG signals. It converts data from the time domain, which represents how the signal evolves over time, into the frequency domain, which reflects the strength of different neural oscillations [3]. Compared with the traditional Discrete Fourier Transform (DFT), the FFT is computationally more efficient, making it well suited for large EEG datasets and real-time applications [4].

The FFT operates on short data segments, often referred to as epochs, whose length must be equal to 2^n data points (e.g., 256, 512, or 1024 samples). The transformation yields two primary outputs: the power spectrum, which represents the distribution of signal energy across frequencies, and the phase spectrum, which reflects the timing relationships of oscillatory activity. In most EEG research, emphasis is placed on the power spectrum, as it captures key neural rhythms including delta, theta, alpha, beta, and gamma bands [4].

By averaging spectral estimates across multiple epochs, FFT-based analysis reduces the complexity of raw EEG data and produces a stable representation of brain activity. Owing to its computational efficiency and effectiveness, the FFT is widely applied in domains such as brain–computer interfaces, clinical diagnosis, and rehabilitation engineering [3].

2.5.2 Welch's Method for Power Spectral Density Estimation

A common approach for examining neural oscillations in EEG is the estimation of power spectral density (PSD), which describes how signal power is distributed across frequencies. One of the most widely used techniques for PSD estimation is Welch's method, which can be considered a modified and improved version of the FFT [2]. In Welch's method, the EEG signal is segmented into overlapping windows, each of which is windowed and transformed into the frequency domain. The resulting spectra are then averaged, reducing variance and yielding a smoother and more reliable PSD estimate than that obtained from a single FFT [2].

Due to these advantages, Welch's method is extensively used in EEG research, including studies of brain-state classification and event-related neural activity. However, Alam et al. [2] noted that different studies often employ different PSD estimation approaches, such as FFT-based methods, Welch's method, or autoregressive models. These methodological choices can contribute to inconsistencies across findings. Consequently, careful selection, transparent reporting, and methodological consistency in PSD estimation are essential to enhance comparability and reproducibility in EEG research.

2.5.3 Welch's Method

Welch's method estimates the power spectral density (PSD) of EEG signals by dividing the signal into overlapping segments, applying a window function to each segment, computing a periodogram for each windowed segment, and then averaging the resulting spectral estimates. Let the discrete EEG signal be $x(n)$. The signal is divided into L overlapping segments of length M samples with step size D (in samples), such that

$$x_i(n) = x(n + iD), \quad i = 0, 1, \ldots, L-1, \quad n = 0, 1, \ldots, M-1, \tag{2.1}$$

where $x_i(n)$ denotes the ith segment. Overlap occurs when $D < M$, and the total number of segments L depends on the signal length, the window length M, and the step size D [3].

For each segment, a modified periodogram is computed as

$$P_i(f) = \frac{1}{MU} \left| \sum_{n=0}^{M-1} x_i(n)\, w(n)\, e^{-j2\pi f n} \right|^2, \tag{2.2}$$

where $w(n)$ is a window function (e.g., Hamming or Hann) applied to reduce spectral leakage, and U is a normalization factor that corrects for the change in signal power introduced by windowing. Here, MU denotes the product $M \cdot U$, and U is defined as

$$U = \frac{1}{M} \sum_{n=0}^{M-1} w^2(n). \tag{2.3}$$

Finally, the Welch PSD estimate is obtained by averaging the periodograms across the L segments:

$$P_{\text{Welch}}(f) = \frac{1}{L} \sum_{i=1}^{L} P_i(f). \tag{2.4}$$

This averaging reduces the variance of the spectral estimate and typically yields a smoother PSD than a single FFT-based periodogram [3] (see figure 2.1).

2.5.4 Logarithmic Transformation (dB Scale)

In EEG analysis, power values are commonly converted to a logarithmic scale, expressed in decibels (dB), to improve interpretability and normalize the data distribution. The logarithmic transformation is defined as

$$P_{\text{dB}} = 10 \log_{10}(P), \tag{2.5}$$

where P represents the power at a given frequency and P_{dB} is the corresponding log-transformed value. Expressing power in decibels compresses large numerical differences, facilitating comparisons across participants, conditions, and recording sessions [2].

In summary, EEG spectral analysis involves transforming raw time-domain signals into frequency-domain representations that reveal underlying neural oscillations. The Fast Fourier Transform (FFT) provides a rapid and efficient means of computing the power spectrum, while Welch's method extends this approach by averaging across overlapping segments to yield smoother and more reliable power spectral density estimates [2]. Finally, logarithmic transformation using the dB scale enhances interpretability and helps normalize power distributions across individuals and experimental conditions. Together, these techniques form the foundation of modern EEG frequency analysis and are widely used in both research and clinical applications [2].

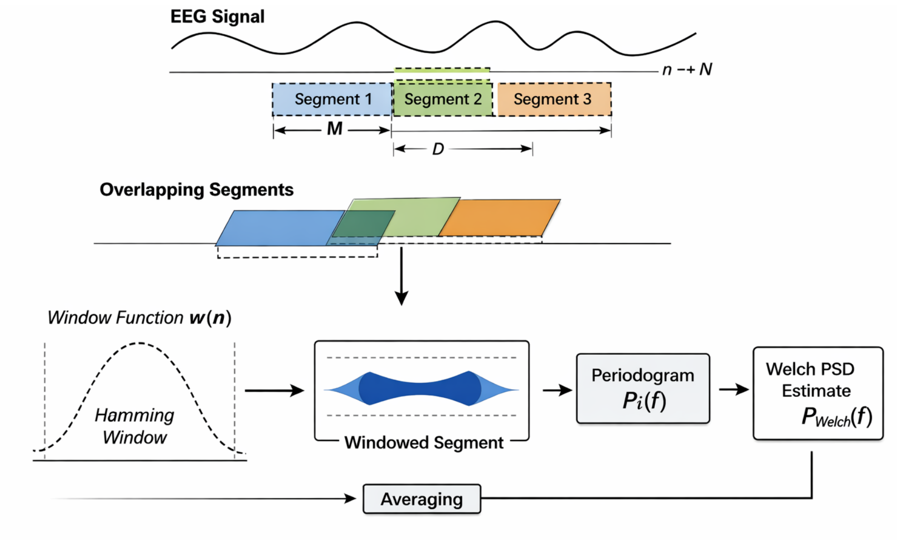

Figure 2.1: Welch's method windowing for power spectral density (PSD) estimation. A continuous EEG signal is segmented into overlapping windows (length M, step D). Each segment is tapered with a window function $w(n)$ (e.g., Hamming or Hann), its periodogram is computed, and the spectra are averaged to obtain the final PSD.

2.6 Artifacts in EEG

Electroencephalography (EEG) signals capture neural activity but can also contain noise from non-neural sources, such as eye movements, eye blinks, and muscle activity [46, 81]. These artifacts can reduce data quality and, if not properly managed, may affect the interpretation of findings in frontal EEG asymmetry research [4]. x *Ocular artifacts* occur when electrical activity generated by the eyes, caused by blinks or eye movements, spreads to scalp electrodes. The eyes possess a natural electrical polarity, and changes in gaze direction alter the surrounding electrical field, which can be detected in EEG recordings [41, 48]. Most ocular artifact energy is concentrated in low-frequency bands, particularly delta and theta, although some overlap can occur with the alpha band commonly used in asymmetry studies [54]. Evidence suggests that ocular artifacts tend to spread relatively symmetrically across hemispheres, resulting in a limited effect on alpha asymmetry indices [48]. However, frontal pole electrodes are more susceptible to contamination, and frequent blinks or eye movements may still influence the relationship between EEG measures and behavioural or psychological outcomes.

Facial muscle activity represents another common source of EEG contamination [20, 40], typically measured using facial electromyography (EMG). Although facial EMG power is predominantly expressed at higher frequencies, some activity

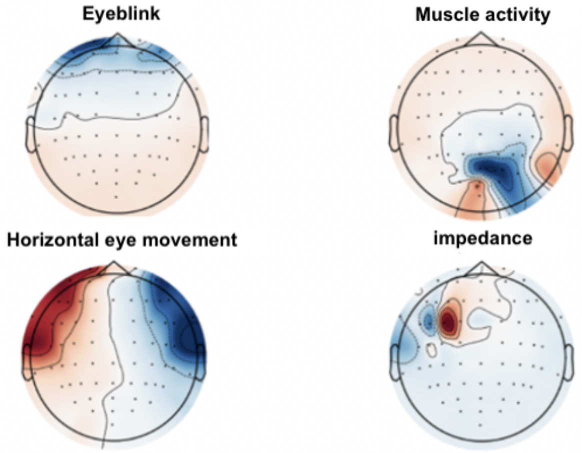

Figure 2.2: Typical topographic patterns of ocular, muscular, and impedance-related EEG artifacts.

may extend into the alpha range. In addition, facial EMG can exhibit asymmetries that resemble cortical activation patterns [17]. Studies that statistically adjust EEG data for facial EMG variance often report minimal changes in primary results [25, 28]. Nevertheless, muscle activity originating from the forehead or temporal regions, particularly during facial expressions or speech, can overlap with signals recorded by nearby EEG electrodes.

Other sources of noise include changes in electrode impedance and electrical activity associated with the heartbeat, both of which can generate misleading scalp patterns if not identified and corrected [3].

Recognizing artifacts in scalp maps is an important step in EEG preprocessing. Figure 2.2 illustrates typical EEG topographic patterns associated with different artifact types. Eye blinks and horizontal eye movements often produce strong activity at frontal or lateral electrode sites, muscle artifacts typically appear over temporal regions, impedance-related artifacts create localized irregular patterns, and heartbeat artifacts show rhythmic activity over central or frontal areas. In contrast, genuine neural signals exhibit spatial distributions consistent with known cortical sources [86]. Accurate recognition of these patterns is essential for reliable preprocessing and subsequent analysis.

Artifact management involves rejecting contaminated data, applying correction methods, or controlling for electrooculographic (EOG) and EMG influences. EOG activity from eye movements and blinks can contaminate frontal EEG channels. While these artifacts may not strongly affect alpha asymmetry, they can bias frontal signals, making careful detection and handling essential [3].

2.7 Independent Component Analysis (ICA) for Artifact Removal

Independent Component Analysis (ICA) is a widely used technique for separating EEG data into statistically independent components, allowing researchers to identify and remove artifacts such as eye blinks, horizontal eye movements, and muscle activity. ICA assumes that the recorded EEG signals are linear mixtures of independent neural and non-neural sources, which can be unmixed through statistical decomposition [37].

The ICA-based artifact removal procedure typically involves several key steps:

- **Preprocessing**: Filtering and down-sampling the EEG data to improve signal quality and prepare the dataset for decomposition.
- **ICA Decomposition**: Decomposing the EEG signal into independent components, each characterized by a distinct spatial topography and temporal activation pattern.
- **Component Identification**: Inspecting component scalp maps, time courses, and spectral properties to identify components associated with artifacts (e.g., strong frontal topographies for eye blinks or lateralized patterns for horizontal eye movements).
- **Artifact Removal**: Removing the identified artifact-related components and reconstructing the cleaned EEG signal from the remaining components.

This approach enables selective removal of non-neural activity while preserving neural signals of interest, making ICA a standard preprocessing step in modern EEG analysis pipelines (see Figure 2.3).

2.8 Computational Perspective: EEG Feature Extraction, Multimodal Integration, and Reproducible Pipelines

From a computer science perspective, EEG-based exercise research can be framed as a data-pipeline problem in which high-dimensional time-series recordings must be transformed into stable, interpretable features that support statistical comparisons and brain–behavior analyses. Raw scalp EEG has a low signal-to-noise ratio and is commonly contaminated by non-neural sources such as eye movements and muscle activity. As a result, the validity of downstream spectral measures depends strongly on standardized preprocessing and transparent reporting of analytical choices. In studies that focus on oscillatory activity, a typical pipeline includes filtering and channel selection, artifact identification and correction, spectral estimation, and feature aggregation. Each stage reduces complexity while aiming to preserve

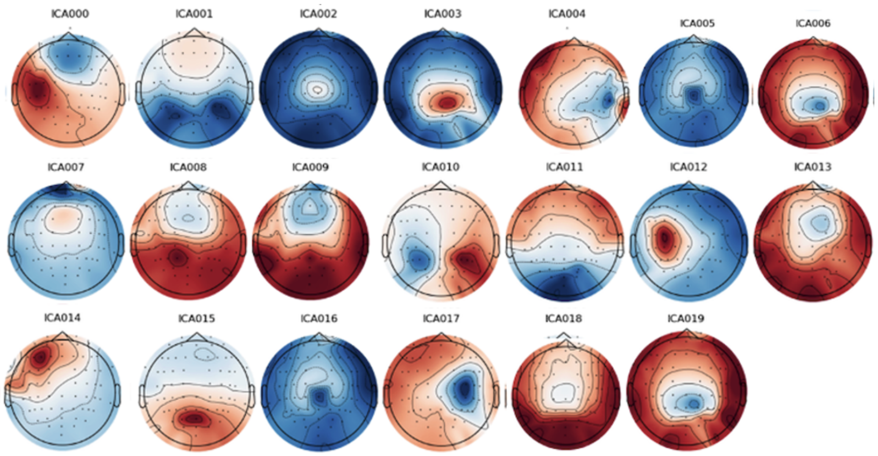

Figure 2.3: Example independent component scalp maps used for artifact identification.

physiologically meaningful neural information, ultimately producing a structured dataset suitable for hypothesis testing.

In the present thesis, this computational framing is directly aligned with the study design and research question. EEG was recorded in standardized states (rest and a computerized task) at two timepoints (pre- and post-exercise) for two HIIT prescriptions, and the analysis required that all recordings be processed consistently to enable within-subject contrasts. Accordingly, the workflow converts continuous EEG recordings into band-limited features by estimating power spectral density using FFT- and Welch-based approaches and summarizing activity within canonical frequency bands (theta, alpha, and beta). Because spectral estimates can be biased by artifacts, Independent Component Analysis (ICA) is used as an essential intermediate step to reduce structured noise sources prior to feature extraction. The resulting features are then expressed in comparable units (including log-transformed power in dB when appropriate) and summarized as pre-to-post change scores (POST − PRE) for each condition and state. These change scores provide a compact representation of exercise-related neural modulation that can be compared between protocols and related to perceptual and mood outcomes.

A second computational requirement in this work is multimodal integration. The perceptual and mood measures (e.g., PACES, RPE, Feeling Scale, and POMS) represent complementary outcome variables that must be aligned with EEG-derived features at the participant and session level. This motivates a structured data representation in which each observation corresponds to a participant × protocol × timepoint × state combination, with associated EEG feature vectors and questionnaire variables. The within-subject crossover design supports this integration by allowing protocol comparisons to be made using paired contrasts, reducing the influence of stable individual differences. Finally, reproducibility considerations are addressed by retaining raw EEG files unchanged, exporting intermediate derivatives (cleaned EEG, feature tables, and statistical outputs), and documenting key methodological decisions (e.g., preprocessing parameters, PSD estimation settings, artifact handling, and statistical test selection rules). Together, these principles position the thesis within a broader research landscape where sports-science questions about HIIT prescription are answered using transparent signal-processing pipelines and statistically controlled inference on extracted EEG features.

Chapter 3

Methodology

3.1 Proposed Framework and Experimental Protocol Overview

This study followed a within-subject crossover framework in which each participant completed two HIIT conditions (“Psychological” and “Physiological”) on separate visits, allowing protocol effects to be evaluated while controlling for stable inter-individual variability. Untrained female participants (age ≥ 18) were recruited and screened using standardized health and eligibility forms (screening interview, informed consent, PAR-Q+, and GIQ), and only participants meeting inclusion criteria and without contraindications to maximal or submaximal exercise were enrolled. The protocol consisted of four laboratory visits completed in the Sports Studies Laboratory, with visits separated by 48 hours to seven days. Visit 1 determined maximal aerobic speed (MAS), Visit 2 determined time limit at MAS (t_{lim}), and Visits 3 and 4 comprised the two HIIT sessions delivered in randomized order.

During each HIIT visit, EEG was recorded at two standardized timepoints (pre-exercise and post-exercise) under two states: seated resting and a computerized attention task (Tetris). EEG was acquired using a 64-channel actiCAP/actiCHamp system (Brain Products GmbH) positioned according to the international 10–20 system, recorded at 1000 Hz, referenced to FCz during acquisition and re-referenced offline to a common average. Electrode impedances were maintained below 20 kΩ, and event markers were synchronized with the EEG stream to label recording segments and task periods. In parallel, perceptual outcomes (PACES, RPE, Feeling Scale) and mood (POMS) were collected at standardized timepoints to enable integration of neurophysiological and subjective responses.

All data were de-identified and stored in a structured directory organized by participant identifier and visit/condition, with separate folders for raw EEG recordings, processed EEG outputs, and tabulated questionnaire measures. Raw EEG files were retained unchanged, and all preprocessing outputs and analysis tables were exported as separate derivative files to support traceability and reproducibility. The detailed participant criteria, visit procedures, and analysis steps are described in Sections 3.1–3.3.

3.2 Data Description

The dataset comprises synchronized neurophysiological and self-report measures collected during two HIIT sessions (“Psychological” and “Physiological”) in a within-subject crossover design. The primary physiological signal is scalp EEG acquired with a 64-channel actiCAP/actiCHamp system (Brain Products GmbH) sampled at 1000 Hz, with electrodes positioned according to the international 10–20 system. For each HIIT visit, EEG was recorded at two timepoints (PRE and POST) and under two standardized states: a seated resting period and a computerized attention task (Tetris). Accordingly, each participant contributed up to four EEG recordings per condition (PRE–REST, PRE–TETRIS, POST–REST, POST–TETRIS). In addition to EEG, perceptual and affective variables were collected using validated instruments, including the Profile of Mood States (POMS; pre- and post-session), the Physical Activity Enjoyment Scale (PACES; post-session), and session-level ratings of perceived exertion (RPE; 0–10) and affective valence (Feeling Scale; -5 to $+5$), enabling integration of neural and subjective responses.

The analytical features derived from EEG focused on oscillatory activity in established frequency ranges, specifically theta (4–7 Hz), alpha (8–13 Hz), and beta (13–30 Hz). For each participant, condition, channel, and state, power spectral density (PSD) was estimated from cleaned EEG data using Welch’s method, and band-limited power was computed by averaging PSD values within each target band. Power was expressed on a logarithmic (dB) scale to improve interpretability and comparability across participants and sessions. The primary EEG outcome variable was the pre-to-post change score (ΔPower = POST $-$ PRE), computed separately for REST and Tetris and, for some analyses, averaged across states to produce a single condition-level change estimate. A secondary derived feature was frontal asymmetry, computed as the right-minus-left difference in power across homologous frontal electrode pairs, with asymmetry change computed as ΔFA = POST $-$ PRE.

Data were organized and stored in a structured directory by participant identifier and condition, with raw EEG recordings retained unchanged and all processing outputs saved as derivative files to support traceability. Questionnaire data were stored in tabulated format and merged with EEG-derived features by participant and condition for statistical testing and exploratory association analyses. Preprocessing and transformations prior to final analysis included band-pass filtering (1–60 Hz), removal of non-EEG channels, bad-channel detection and interpolation, and ICA-based artifact correction to reduce ocular and muscle contamination. Following preprocessing, spectral estimation, log transformation, and the computation of change scores (POST $-$ PRE) constituted the main transformations applied before statistical comparison between HIIT protocols.

3.3 Participants

A total of 20 untrained female participants (age ≥ 18 years) were recruited through the researchers' professional network and word-of-mouth referrals. All participants completed a standardized eligibility screening prior to their first laboratory visit and provided written informed consent before taking part in any study procedures.

Before Visit 1, eligibility and health status were assessed using four documents: a screening interview, an informed consent form, the 2020 Physical Activity Readiness Questionnaire (PAR-Q+) from the Canadian Society for Exercise Physiology, and an in-house General Information Questionnaire (GIQ). Participants were included if they were biologically female, at least 18 years old, able to communicate in English or French, and untrained in endurance running, defined as not having followed a systematic running program (self-guided or supervised) for at least four consecutive weeks and not having breaks longer than 14 days. Participants were excluded if they reported medical conditions contraindicating maximal or submaximal exercise based on the PAR-Q+, a medically diagnosed cardiovascular disease, or acute/chronic musculoskeletal injuries that could compromise safe participation in treadmill testing or HIIT sessions. When an injury or medical concern was identified, participants were advised to consult a health-care provider to confirm whether participation was safe.

The GIQ was used to characterize the sample by collecting demographic information (e.g., age, height, and weight), exercise and injury history, menstrual-cycle information, pregnancy-related exercise experiences (if applicable), pelvic-floor symptoms, gastrointestinal health, and menstrual function. Participation was voluntary and participants could withdraw at any time without penalty. Ethical approval was obtained from the Bishop's University Research Ethics Board (Protocol No. 102842), and all procedures were conducted in accordance with the Declaration of Helsinki.

3.4 Procedures

The experimental protocol consisted of four laboratory visits conducted in the Sports Studies Laboratory, where the treadmill and EEG systems were located. Visits were separated by a minimum of 48 hours and a maximum of seven days to allow adequate recovery while maintaining scheduling consistency. All running tests and HIIT sessions were performed on a Woodway treadmill (4Front, Waukesha, WI, USA).

Visit 1 was used to determine each participant's maximal aerobic speed (MAS) using a graded treadmill test. Visit 2 assessed the individual time limit at MAS (t_{lim})

by having participants run continuously at their MAS until volitional exhaustion. Visits 3 and 4 consisted of two randomized HIIT sessions: a fixed-bout protocol ("Psychological" HIIT) and an individualized-bout protocol ("Physiological" HIIT). The order of these two HIIT visits was counterbalanced across participants as described below.

The order of Visits 3 and 4 was randomized using block randomization to minimize order effects. Both HIIT protocols were matched for total duration (3-minute warm-up, approximately 20-minute main exercise bout, and 2-minute cool-down; ~25 minutes total), exercise intensity (MAS), work-to-rest ratio (1:1), warm-up and cool-down intensity (60% MAS), and treadmill grade (1%).

The following measures were collected at standardized time points across visits:

- **Heart Rate (HR).** continuously monitored (visits 1–4) during treadmill running tests (goal: confirm individuals reached their maximal effort).

- **Rating of Perceived Exertion (RPE).** Borg 6–20 scale or Borg 0–10 scale [15] recorded at specific times during each test (visits 1 and 2 = Borg 6–20 scale; goal: confirm individuals reached their maximal effort) or training sessions (visits 3 and 4 = Borg 0–10 scale; goal: determine session RPE based on measurements taken throughout the session in pre-set time points).

- **Pleasure/Displeasure (Feeling Scale).** collected during HIIT sessions in pre-set time points (visits 3 and 4). We used the −5 (most unpleasant) to +5 (most pleasant) Feeling Scale, and averages for each HIIT session were reported for analysis [51].

- **Profile of Mood States (POMS).** completed pre- and post-HIIT sessions (visits 3 and 4). We applied the POMS questionnaire originally developed [67]. The questionnaire allowed us to calculate five negative mood dimensions (confusion, anger, depression, tension, and fatigue) and one positive mood dimension (vigour). Higher values represent a greater predominance of a given mood dimension. To complete mood state analysis, we summed the five negative scales and subtracted the positive one. To this result, we added 100 to avoid negative numbers. This score is called Total Mood Disturbance (TMD), and the greater it is, the worse the individual's mood state.

- **Physical Activity Enjoyment Scale (PACES).** Completed following each HIIT session (Visits 3 and 4) [56]. Scores range from 18 to 126, with higher values indicating greater enjoyment.

- **Electroencephalography (EEG).** EEG data were collected using an actiCAP slim system (Brain Products GmbH, Gilching, Germany) with 64 active Ag /AgCl electrodes positioned according to the international 10–20 system. Electrode impedance was maintained below 20 kΩ for all channels. Signals were referenced to FCz during acquisition and re-referenced to the common average offline.

Role of the Tetris condition In addition to a seated resting recording, a brief computerized task (Tetris) was included before and after each HIIT session to provide a standardized cognitive engagement period. Importantly, Tetris was not used as a validated or diagnostic measure of attention; rather, it served as a practical, repeatable task that reliably keeps participants visually engaged under consistent instructions. The purpose of this condition was to complement resting-state EEG with a task context in which attention, monitoring, and mental effort are more consistently engaged across participants, thereby offering a second and more controlled measurement state for post-exercise EEG. Practically, this approach also helped reduce extended passive sitting and uncontrolled variability in mental state during recording (e.g., boredom, mind-wandering, or drowsiness), which can substantially influence oscillatory activity during "rest" even when participants remain seated and quiet. From a neurophysiological perspective, task engagement has been associated with changes in fronto-central oscillatory dynamics, including theta activity, which has been linked to cognitive control and performance monitoring [21, 95]. The same task timing and procedure were applied at both PRE and POST recordings to support within-subject comparability across timepoints and protocols. Accordingly, EEG outcomes were computed separately for REST and Tetris (PRE and POST) and, for the primary topographic analyses, were also summarized using a state-averaged index (REST+Tetris) to capture overall post-exercise change while reducing dependence on any single recording context.

EEG signals were amplified using an actiCHamp Plus amplifier (Brain Products GmbH, Germany) with 24-bit analog-to-digital conversion and recorded at a sampling rate of 1,000 Hz. The system provided high input impedance (>1 GΩ) and low noise. Experimental event markers were synchronized with the EEG stream via the amplifier's marker input. EEG recordings were obtained during pre- and post-HIIT sessions in Visits 3 and 4 (see Figure 3.1).

3.4.1 Visit 1: Baseline and MAS Assessment

The first laboratory visit aimed to determine each participant's maximal aerobic speed (MAS) using a maximal incremental treadmill test.

Participants began with a 3-minute warm-up at 6 km·h^{-1}. The test started at a speed of 8 km·h^{-1}, with treadmill speed increasing by 1 km·h^{-1} every 3 minutes until volitional exhaustion was reached [63]. The treadmill grade was set at 1% for the entire duration of the test. Heart rate (H10 Polar, Kempele, Finland) and rating of perceived exertion (RPE; Borg 6–20 scale) [15] were recorded near the end of each stage (approximately 2 minutes and 45 seconds). Maximal effort was confirmed when participants achieved both a heart rate $\geq$95% of age-predicted maximal heart

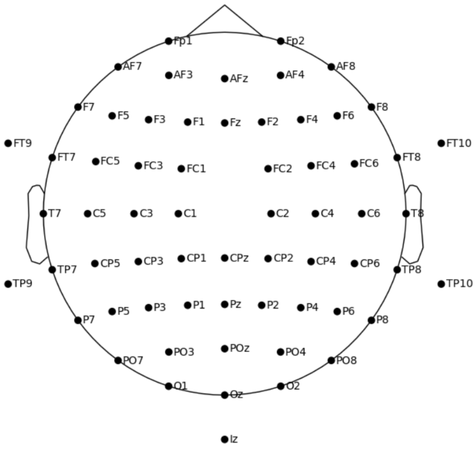

Figure 3.1: Standard 10–20 EEG electrode placement system.

rate (calculated as 220 − age) and an RPE value ≥18. The test was terminated when the participant was unable to maintain the required running speed despite verbal encouragement.

MAS was determined using one of the following approaches:

- **Direct MAS**: If the participant completed the final stage in full, MAS was defined as the running speed of that stage.
- **Estimated MAS**: If the final stage was not completed, MAS was calculated using the following equation [62, 63]:

$$\text{MAS} = V_{\text{last}} + \frac{t_{\text{final}}}{180} \cdot \Delta V \tag{3.1}$$

  where V_{last} is the speed of the last fully completed stage (km/h), t_{final} is the time (in seconds) completed in the final, incomplete stage, and ΔV is the speed increment between stages (1 km/h).

3.4.2 Visit 2: Individual's Time Limit (t_{lim}) Test

The objective of the second laboratory visit was to determine each participant's time limit (t_{lim}) when running continuously at the MAS obtained during Visit 1.

Participants began with a 10-minute warm-up at 60% of their MAS. Immediately after, they ran continuously at their MAS speed until they reached voluntary exhaustion [26]. Treadmill grade was also kept constantly at 1%. Heart rate and RPE were recorded near the end of each minute to verify that maximal effort was achieved, following the same criteria used in Visit 1.

The total running time at MAS, measured in minutes, was recorded as the participant's t_{lim}. This value was subsequently used to determine the individualized work-bout duration for the "Physiological" HIIT protocol.

3.4.3 Visits 3 and 4: Randomized HIIT Protocols ("Psychological" and "Physiological")

Visits 3 and 4 were used to complete two treadmill-based HIIT sessions: "Psychological" HIIT and "Physiological" HIIT. The order of these sessions was randomized for each participant to minimize order effects. Both protocols were matched for total duration (~25 minutes), exercise intensity (MAS), warm-up and cool-down procedures, work-to-rest ratio (1:1), and treadmill incline (1%). The only difference between protocols was how the high-intensity bout duration was defined: fixed 1-minute intervals for the "Psychological" HIIT and 60% of the individual's $\mathrm{t_{lim}}$ for the "Physiological" HIIT. This adjustment consequently influenced the number of bouts performed by each participant. Each visit lasted approximately 90 minutes to accommodate all measurements.

Pre-Exercise Procedures At the beginning of each visit, EEG setup was performed and required approximately 20 minutes. Once the EEG system was in place, a 15-minute pre-exercise recording was collected, consisting of: The pre-exercise recording consisted of 5 minutes of seated rest followed by 10 minutes of a computerized attention task (Tetris).

HIIT Protocols Participants completed both HIIT sessions while wearing the EEG cap (temporarily disconnected during exercise). Heart rate was continuously monitored using the Polar Beat app (Polar, Kempele, Finland). Ratings of Perceived Exertion (RPE; 0–10) were collected at specific intervals during exercise and later averaged for analysis.

- **"Psychological" HIIT:** Started with a 3-minute warm-up at 60% MAS, followed by 10×1-minute running bouts at 100% MAS. Each bout was followed by 1 minute of passive recovery (1:1 ratio). The session ended with a 2-minute cool-down at 60% MAS, for a total duration of approximately 25 minutes.
- **"Physiological" HIIT:** Used the same warm-up and cool-down procedures but individualized the work intervals. Each high-intensity bout lasted 60% of the participant's time limit at MAS (t_{lim}; measured in Visit 2), followed by an equal duration of passive recovery. The number of intervals was adjusted so that the total main exercise time matched the "Psychological" HIIT (approximately 20 minutes for the main part and 25 minutes total).

Post-Exercise Procedures After completing the treadmill session, a 15-minute post-exercise EEG recording was collected, consisting of 5 minutes of seated rest followed by 10 minutes of the Tetris task (see Figure 3.2).

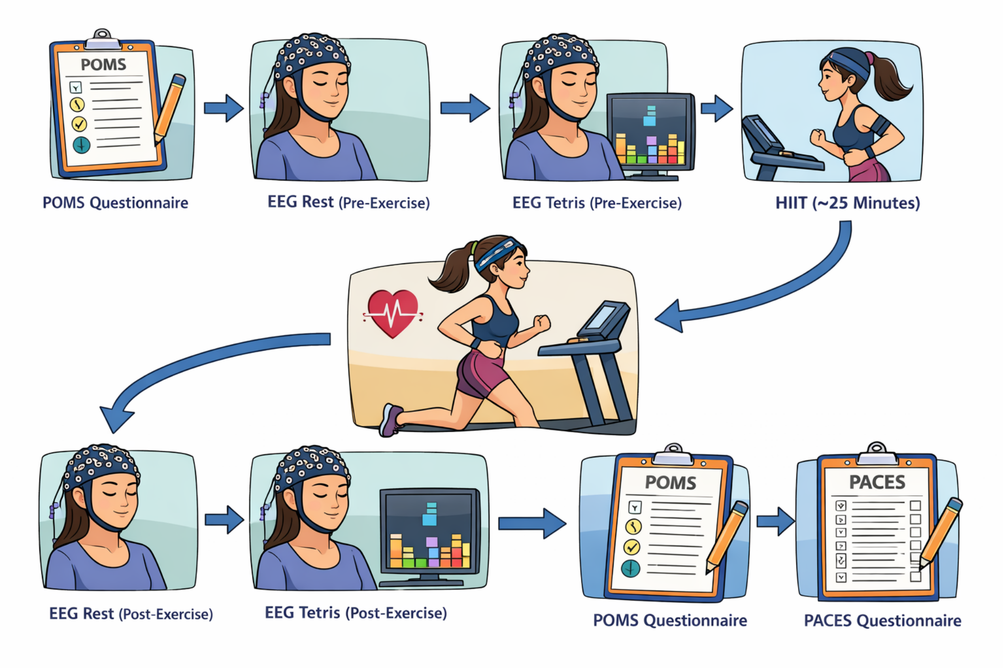

Figure 3.2: Experimental timeline of a HIIT session.

3.5 Data Analysis

The perceptual and EEG datasets were analyzed in six sequential computational phases: (1) processing of perceptual data, (2) preprocessing and cleaning of EEG signals, (3) detection and removal of artifacts using Independent Component Analysis (ICA), (4) computation of spectral power and extraction of relevant features, (5) statistical analysis, and (6) integration of EEG and perceptual datasets for combined interpretation.

All analyses were performed in Python using a modular, object-oriented pipeline, employing established scientific computing libraries, including MNE-Python, SciPy, NumPy, Statsmodels, Pandas, and Matplotlib for statistical modeling and data visualization.

3.5.1 Perceptual Data Processing and Analysis

Raw perceptual measures, including enjoyment (PACES), rating of perceived exertion (RPE), Feeling Scale scores, and Profile of Mood States (POMS) subscales, were compiled into structured spreadsheets and imported into Python for analysis. Data from the two HIIT conditions were loaded as separate data frames:

Perceptual data for the Psychological and Physiological sessions were imported into Python as separate data frames and then harmonized by participant identifier and condition. The corresponding code is provided in Appendix A.1.

Data were harmonized by participant identifier and HIIT condition ("Psychological" or "Physiological"). For mood-related outcomes, pre-to-post changes (Δ) were computed programmatically for each POMS subscale (Tension, Depression, Anger, Fatigue, Confusion, and Vigour), as well as for Total Mood Disturbance (TMD). Normality of each variable was assessed using the Shapiro–Wilk test. Based on the normality results, paired t-tests were applied for normally distributed variables, while Wilcoxon signed-rank tests were used for non-normally distributed variables to compare conditions within subjects.

Visualization followed the same decision rule. Normally distributed variables were displayed using bar plots (mean ± SD), whereas non-normally distributed variables were visualized using box plots (median, interquartile range, and whiskers spanning the 5th to 95th percentiles). Individual participant data points were overlaid as small scattered dots with a slight horizontal offset to illustrate inter-individual variability.

Figures were organized as follows: Figure 4.1 presents PACES, mean RPE, and Feeling Scale outcomes in three panels, whereas Figure 4.2 presents POMS change scores (Δ = Post − Pre) for Tension, Depression, Anger, Fatigue, Confusion, and Vigour, along with Total Mood Disturbance (TMD), displayed across two rows of three panels for the mood subscales and a third row containing a single panel for TMD.

3.5.2 EEG Signal Preprocessing

EEG preprocessing was performed in MNE-Python using a standardized pipeline to improve signal quality prior to ICA and spectral analysis. Continuous data were band-pass filtered between 1–60 Hz with a finite impulse response (FIR) filter using a Hamming window to attenuate slow drifts and high-frequency noise. Non-EEG sensors were excluded so that subsequent analyses were restricted to EEG channels only. Bad channels were identified based on abnormal signal variance (z-score > 3) and were then interpolated using spherical spline interpolation. This preprocessing produced a clean and consistent EEG dataset suitable for artifact decomposition and band-power estimation.

3.5.3 ICA-Based Artifact Removal

Independent Component Analysis (ICA) was employed to identify and remove structured EEG artifacts, including ocular activity (e.g., blinks and saccades) and muscle-related noise. The ICA procedure consisted of the following steps:

For ICA-based artifact removal, EEG recordings from all four experimental states (PRE–REST, PRE–TETRIS, POST–REST, and POST–TETRIS) were concatenated within each participant and condition to improve the stability of the decomposition. The concatenated data were re-referenced to the standard 10–20 montage

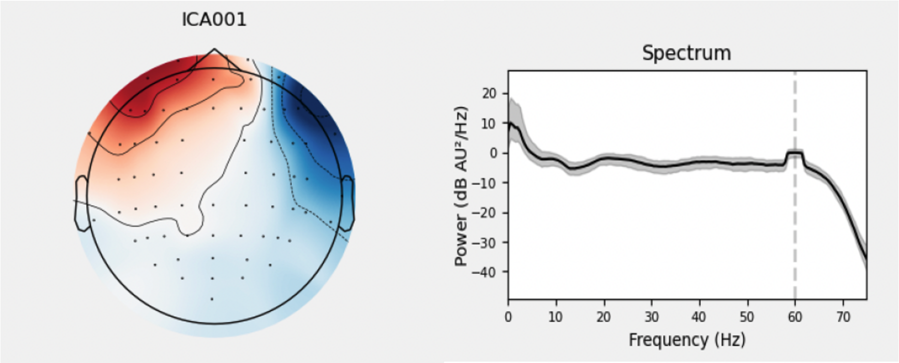

Figure 3.3: Representative ICA artifact component removed from the EEG data. The scalp map shows a frontal-dominant projection, and the activation time course includes large transient deflections characteristic of ocular activity (eye blinks/eye movements). The component's spectral profile is dominated by low-frequency power, indicating potential inflation of frontal low-frequency activity in the reconstructed EEG.

and band-pass filtered between 1–60 Hz prior to ICA. For each participant, 50 independent components were extracted. Components were then visually inspected using their scalp topographies, activation time courses, and spectral profiles to identify artifact-related sources (e.g., ocular or muscle activity). Identified artifact components were removed and the cleaned EEG signals were reconstructed and saved for subsequent analyses.

Example of removed ICA component Figure 3.3 shows a representative independent component that was removed during preprocessing. This component displays a strong frontal scalp projection and large transient deflections in its activation time course, consistent with ocular activity (eye blinks/eye movements). Because ocular artifacts are dominated by low-frequency energy and project strongly to frontal electrodes, retaining them can artificially increase frontal low-frequency power and bias comparisons of post-exercise changes, particularly in the theta band. After excluding this component and reconstructing the data, these non-neural transients were visibly reduced in frontal channels, improving the interpretability of subsequent spectral power analyses

3.5.4 Spectral Power Computation

For each participant, EEG frequency band, and electrode, power spectral density (PSD) values were estimated at pre- and post-exercise time points using Welch's method. Power values were converted to decibels (dB) and averaged across frequency bins corresponding to the target frequency bands: theta (4–7 Hz), alpha (8–13 Hz), and beta (13–30 Hz).

For each electrode c, frequency band b, condition (PS or PH), and recording state $s \in \{\text{REST}, \text{TETRIS}\}$, the change in spectral power between post- and pre-exercise was computed as:

$$\Delta P(b,c) = P_{\text{POST},s}(b,c) - P_{\text{PRE},s}(b,c) \tag{3.2}$$

In practice, band-limited power was computed in Python following the procedure described in Appendix A.2.

3.5.5 EEG–Behavior Correlation Analysis

To examine whether protocol-specific neural changes covaried with affective and perceptual outcomes, we performed within-condition correlation analyses between EEG band-power change and questionnaire-based measures. EEG power was first summarized as a pre-to-post change score (ΔPower = POST − PRE) at the channel level, after averaging power across REST and TETRIS within each timepoint. Next, for each frequency band (theta, alpha, beta), analyses were restricted to a predefined set of electrodes identified as significant in the corresponding topographic contrast (PS vs. PH). For each participant and condition, ΔPower values were averaged across these band-specific electrodes to obtain a single summary predictor per band (e.g., $\Delta\text{Power}_{\theta,\text{sig}}$), enabling a reduced-dimensionality EEG metric for correlation testing.

Behavioral variables included session-level enjoyment (PACES), mean perceived exertion (RPE), mean affective valence (Feeling Scale), and pre-to-post mood changes derived from POMS subscales (POST − PRE). EEG summaries and behavioral variables were merged by participant identifier and condition (PS or PH), and correlations were computed separately within each protocol (PS and PH) to avoid conflating between-condition differences with within-condition associations. For each band–outcome pair, participants with missing data in either variable were excluded listwise for that specific test.

For inferential choice, normality of each variable was evaluated using the Shapiro–Wilk test within the available sample for that condition. If both the EEG predictor and the behavioral outcome were approximately normal (Shapiro–Wilk $p > 0.05$ for each), Pearson's correlation coefficient (r) was reported; otherwise Spearman's rank correlation (ρ) was used. To reduce unstable estimates, correlations were computed only when at least five paired observations were available for a given condition and variable combination. For visualization, scatter plots were produced separately for each band and outcome, with PS and PH shown in separate colors, and a least-squares line overlaid for each condition to aid interpretation; correlation coefficients, p-values, and sample sizes were retained in a summary results table for reporting.

Outliers and statistical validity Correlation analyses were treated as exploratory and interpreted with caution due to the modest sample size and the possibility that a small number of participants could exert disproportionate influence on bivariate associations. To reduce bias from missingness, each correlation was computed using only participants with complete data for the specific band–outcome pair, and analyses were stratified by condition (PS vs. PH) to avoid mixing protocol-level differences with within-condition relationships. As a basic robustness safeguard, we required a minimum number of paired observations (at least five) prior to reporting any correlation. In follow-up sensitivity checks (reported as supplementary material when applicable), associations can be re-estimated after inspecting scatter plots for influential points and repeating correlations with robust alternatives (e.g., Spearman rank correlations, or correlations computed after excluding a single high-leverage observation) to evaluate whether the direction and approximate magnitude of effects are stable.

3.5.6 Statistical Analysis

The statistical analysis phase aimed to determine whether changes in EEG power (ΔPower = POST − PRE) differed between the two HIIT protocols ("Psychological" and "Physiological") and to identify which scalp regions and frequency bands showed significant effects.

In Results Sections 4.2–4.4, analyses focused on changes in EEG spectral power (ΔP) computed for each participant, electrode, and frequency band as the difference between post- and pre-exercise. For the main topographic analyses, ΔP was calculated using the mean ΔPower averaged across both REST and TETRIS states for each participant:

$$\Delta P(b,c) = \frac{\Delta P_{\mathrm{REST}}(b,c) + \Delta P_{\mathrm{TETRIS}}(b,c)}{2}, \tag{3.3}$$

where b denotes the frequency band and c denotes the EEG channel.

This averaged index $\Delta P(b,c)$ was used to generate the topographical scalp maps shown in Figures 4.3– 4.5 and to perform paired comparisons between "Psychological" (PS) and "Physiological" (PH) HIIT sessions for each frequency band.

Normality testing and test selection Before conducting PS–PH comparisons, normality was assessed using the Shapiro–Wilk test applied separately to the PS and PH distributions for each channel. This step determined whether parametric assumptions were met.

- If both conditions were normally distributed ($p > 0.05$), a paired t-test was used to compare PS and PH values.
- If either condition violated normality ($p \leq 0.05$), a Wilcoxon signed-rank test was used instead.

Correction for multiple comparisons Because each frequency band involved statistical testing across multiple electrodes, the risk of Type I error was addressed using False Discovery Rate (FDR) correction via the Benjamini–Hochberg procedure. Adjusted q-values were computed for each electrode within each band. Electrodes with $q < 0.15$ were considered significant at an exploratory level, and uncorrected results with raw $p < 0.05$ were also displayed to illustrate spatial patterns. Notably, no electrodes met the $q < 0.15$ criterion.

Summary tables and log outputs For each electrode, an automated summary table was generated reporting the Shapiro–Wilk p-values for PS and PH (normality outcomes), the statistical test applied (paired t-test or Wilcoxon), the uncorrected p-value for the PS vs. PH comparison, the FDR-adjusted q-value, and a binary indicator of significance ($p < 0.05$).

Topographical visualization of statistical results To support spatial interpretation, statistical results were visualized using MNE-Python's `plot_topomap` function. For each frequency band (theta, alpha, and beta), three scalp maps were generated: the mean ΔPower (POST − PRE) distribution for the Psychological condition (PS), the mean ΔPower distribution for the Physiological condition (PH), and a difference map representing PS − PH. Channel coordinates were obtained from the standard 10–20 electrode layout using a representative BrainVision header file. A diverging color scale centered at zero was applied, where positive values indicate increased power after exercise (POST > PRE) and negative values indicate decreased power. Electrodes showing statistically significant PS–PH differences ($p < 0.05$) were marked with yellow circles.

Interpretation of results The topographical maps and corresponding summary tables provided a spatial overview of EEG power changes across the scalp and enabled comparison between HIIT protocols within each frequency band. These results are reported in the frequency-specific subsections for theta (Section 4.2), alpha (Section 4.3), and beta (Section 4.4). Collectively, this approach allowed identification of band- and region-specific modulations associated with each protocol and supported interpretation alongside the perceptual and mood outcomes presented in the results chapter.

3.5.7 Integration of EEG and Perceptual Datasets for Interpretation of Potential Associations

For correlation figures and summaries (Sections 4.5–4.6), channel-level EEG information was reduced to a single value per band × participant × condition by averaging the state-averaged ΔPower (Sections 4.2–4.4) across the set of electrodes identified as significant in the topographic analyses for each band:

$$\overline{\Delta P}(b,c) = \frac{\Delta P_{\text{REST}}(b,c) + \Delta P_{\text{TETRIS}}(b,c)}{2} \tag{3.4}$$

$$\overline{\Delta P}_b = \frac{1}{|S_b|} \sum_{c \in S_b} \overline{\Delta P}(b,c) \tag{3.5}$$

where S_b denotes the band-specific set of electrodes identified as significant in the topographic analysis.

- **Theta:** AF3, AFz, F1, F7, FC1, C3, C4, C6, FP2, TP8
- **Alpha:** AF3, AFz, TP8
- **Beta:** AFz, F1, FC1, Fz

Perceptual variables were extracted from visit spreadsheets and included enjoyment (PACES), session RPE (0–10), Feeling Scale (−5 to +5), and POMS change scores (POST − PRE) for Tension, Depression, Anger, Fatigue, Confusion, Vigour, and TMD. Datasets were merged by `Participant` and `Condition` (PS or PH).

Correlations were computed separately within each condition (PS, PH) and for each frequency band using the following decision rule .For a given perceptual variable Y and band summary $X = \overline{\Delta P}^{\text{sig}}(b)$:

- If both X and Y passed Shapiro–Wilk normality ($p > 0.05$), Pearson correlation (r) was reported.
- Otherwise, Spearman rank correlation (ρ) was reported.

Scatter plots included fitted regression lines (red = PS; blue = PH). Correlation analyses were treated as exploratory and interpreted alongside exact p-values.

Frontal asymmetry analysis Frontal asymmetry (FA) was computed from homologous left–right electrode pairs: (Fp1–Fp2), (AF3–AF4), (F3–F4), (F5–F6), (F7–F8), (FC3–FC4), (FC5–FC6). The asymmetry convention was defined as:

$$\text{FA} = P_{\text{Right}} - P_{\text{Left}}, \tag{3.6}$$

where positive values indicate right-frontal dominance.

Per-state and per-timepoint FA: For each participant, condition, band, and state ($s \in \{\text{REST}, \text{TETRIS}\}$), FA was computed by averaging across available homologous pairs:

$$FA_{b,s,t} = \frac{1}{K} \sum_{(L,R) \in P} \left(P_{b,R,s,t} - P_{b,L,s,t} \right) \tag{3.7}$$

where K is the number of valid electrode pairs.where P is the set above and K is the number of pairs present for that participant (pairs with a missing channel were skipped).

Change scores were calculated as:

$$\Delta FA = FA_{\mathrm{POST}} - FA_{\mathrm{PRE}}. \tag{3.8}$$

Within each state s, frontal asymmetry change was computed as the difference between post- and pre-exercise values, and a state-agnostic index was obtained by averaging REST and TETRIS deltas.

$$\overline{\Delta \mathrm{FA}_b} = \frac{\Delta \mathrm{FA}_{b,\mathrm{REST}} + \Delta \mathrm{FA}_{b,\mathrm{TETRIS}}}{2}. \tag{3.9}$$

Statistical tests of frontal asymmetry: All FA analyses were performed separately for each frequency band (theta, alpha, beta) and state (REST, TETRIS).

Within-condition PRE vs. POST comparisons: For each HIIT condition ("Psychological" = PS; "Physiological" = PH), we tested whether frontal asymmetry changed from before (PRE) to after (POST) the exercise session within each recording state. For each participant, the within-condition difference

$$FA_{b,s,\mathrm{POST}} - FA_{b,s,\mathrm{PRE}}$$

was computed for each frequency band b and state s. The Shapiro–Wilk test was applied to these paired differences to assess normality. When the distribution of ΔFA values was approximately normal ($p > 0.05$), a paired t-test was used to test whether the mean change differed from zero; otherwise, a Wilcoxon signed-rank test was applied. This approach allowed us to evaluate whether frontal asymmetry increased, decreased, or remained stable within each HIIT protocol for both REST and TETRIS states.

Between-Condition Comparisons on ΔFA per State Next, we assessed whether the change in frontal asymmetry (ΔFA) differed between the two HIIT protocols within each recording state by pairing PS and PH sessions within the same participant. For each participant, ΔFA was computed separately for PS and PH and the paired difference $\Delta FA_{\mathrm{PS}} - \Delta FA_{\mathrm{PH}}$ was then calculated. Shapiro–Wilk normality testing was applied to these paired differences, and either a paired t-test (if normal) or a Wilcoxon signed-rank test (if non-normal) was used to determine whether the two protocols produced significantly different asymmetry changes. This analysis indicated whether one protocol elicited a stronger hemispheric shift than the other within a given state.

Between-Condition Comparisons on State-Averaged ΔFA Finally, to obtain an overall index independent of task state, we computed each participant's average ΔFA across REST and TETRIS and repeated the same between-condition comparison procedure. This test provided a general measure of protocol-related asymmetry effects, summarizing across both states.

Outputs and Interpretation For each frequency band and state, the analysis output included the p-value for within-condition PRE–POST changes (reported separately for PS and PH), the p-value for the between-condition comparison (PS vs. PH) on ΔFA within each state, and the p-value for the between-condition comparison based on the state-averaged ΔFA.

Positive values of ΔFA indicate greater right-frontal dominance post-exercise (i.e., increased relative power in right vs. left homologous electrodes). Accordingly, a positive PS–PH difference suggests a stronger right-frontal activation shift during "Psychological" HIIT compared with "Physiological" HIIT.

Participant Withdrawal and Handling of Dropouts One participant withdrew from the study after completing Visits 1 and 2 due to an injury sustained outside of the experimental sessions. As a result, this participant did not complete either of the HIIT visits (Visits 3 and 4) and had no post-exercise EEG or questionnaire data. Because the study used a within-subject crossover design requiring complete paired observations for both HIIT conditions, this participant's data were excluded from all inferential analyses. All statistical tests were therefore conducted on the final sample of participants who completed the full protocol (i.e., complete-case analysis), and no imputation was performed.

Chapter 4

Results

4.1 Baseline Measures (Pre-Exercise)

A total of n = 20 untrained female participants were included in the final analyses (mean age: *37.54* years). The average maximal aerobic speed (MAS) determined during Visit 1 was *9.7* km/h. The average time limit at maximal aerobic speed (t_{lim} at MAS), measured during Visit 2 and used to prescribe the individualized-bout protocol, was *5.5* minutes. Menstrual history collected during screening indicated that *18 participants reported regular menstrual cycles* and *2 reported irregular cycles;* however, menstrual-cycle phase at the time of testing and hormonal contraceptive use were not systematically recorded in a way that could be modeled in the present analyses. HIIT visits (Visits 3 and 4) were scheduled with a minimum separation of 48 hours and a maximum of seven days; the exact time between sessions varied across participants and was not treated as a predictor in the primary analyses.

Baseline (PRE) measures were collected in both conditions prior to the HIIT session and were used as each participant's within-subject reference point. For perceptual outcomes, baseline mood was assessed using the POMS questionnaire completed immediately before each HIIT session. For EEG outcomes, baseline recordings consisted of two standardized pre-exercise states: 5 minutes of seated rest and 10 minutes of the Tetris task. These baseline recordings were preprocessed

Table 4.1: Mean ± SD of affect responses during "Psychological" and "Physiological" HIIT sessions. *$p < 0.05$ compared with Physiological HIIT.

	Psychological HIIT		Physiological HIIT	
Measure	Mean	SD	Mean	SD
Enjoyment (PACES)	91.35*	24.33	78.10	20.04
RPE Mean	3.94	1.16	4.07	1.12
Feeling Mean	1.91	1.58	1.33	1.42

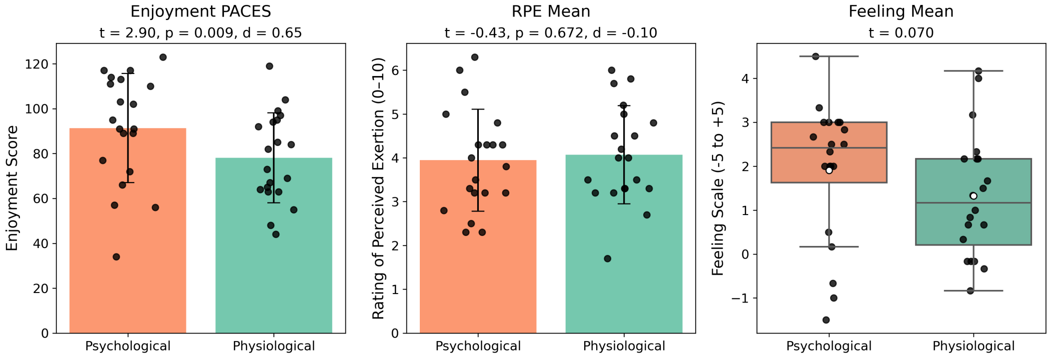

Figure 4.1: Behavioral responses following "Psychological" versus "Physiological" HIIT, including enjoyment (PACES), perceived exertion (RPE; 0–10), and affective valence (Feeling Scale; −5 to +5). Data are shown as mean ± SD with paired t-tests when normality was met; otherwise, boxplots show median and IQR with Wilcoxon signed-rank tests. Black dots indicate paired participant values ($n = 20$), and white circles indicate condition means.

using the same pipeline described in Chapter 3 and served as the PRE term in all subsequent change-score calculations (POST − PRE). Because the study used a within-subject crossover design, baseline comparisons were handled implicitly by analyzing within-participant change from PRE to POST for each condition rather than relying on between-participant baseline matching.

4.2 Perceptual Responses

A series of bar plots and boxplots were used to compare perceptual and affect responses between the "Psychological" and "Physiological" HIIT protocols. Results are summarized in Figures 4.1 and 4.2.

Enjoyment (PACES) was significantly higher following "Psychological" HIIT compared with "Physiological" HIIT ($p = 0.009$), indicating greater positive engagement. No significant differences were observed for session RPE ($p = 0.672$) or affective valence measured by the Feeling Scale ($p = 0.070$), suggesting comparable perceived exertion and pleasure–displeasure responses between protocols. Descriptive statistics are reported in Table 4.1.

Anger scores were significantly lower following the "Psychological" HIIT protocol ($p = 0.040$), indicating a more positive mood response in that dimension. No significant differences were found for Tension ($p = 0.831$), Depression ($p = 0.755$), Fatigue ($p = 0.427$), Confusion ($p = 0.955$), Vigour ($p = 0.058$), or Total Mood Disturbance ($p = 0.286$). Table 4.2 provides a clear view of descriptive statistics for mood dimensions.

In sum, perceptual responses showed that enjoyment (PACES) was significantly

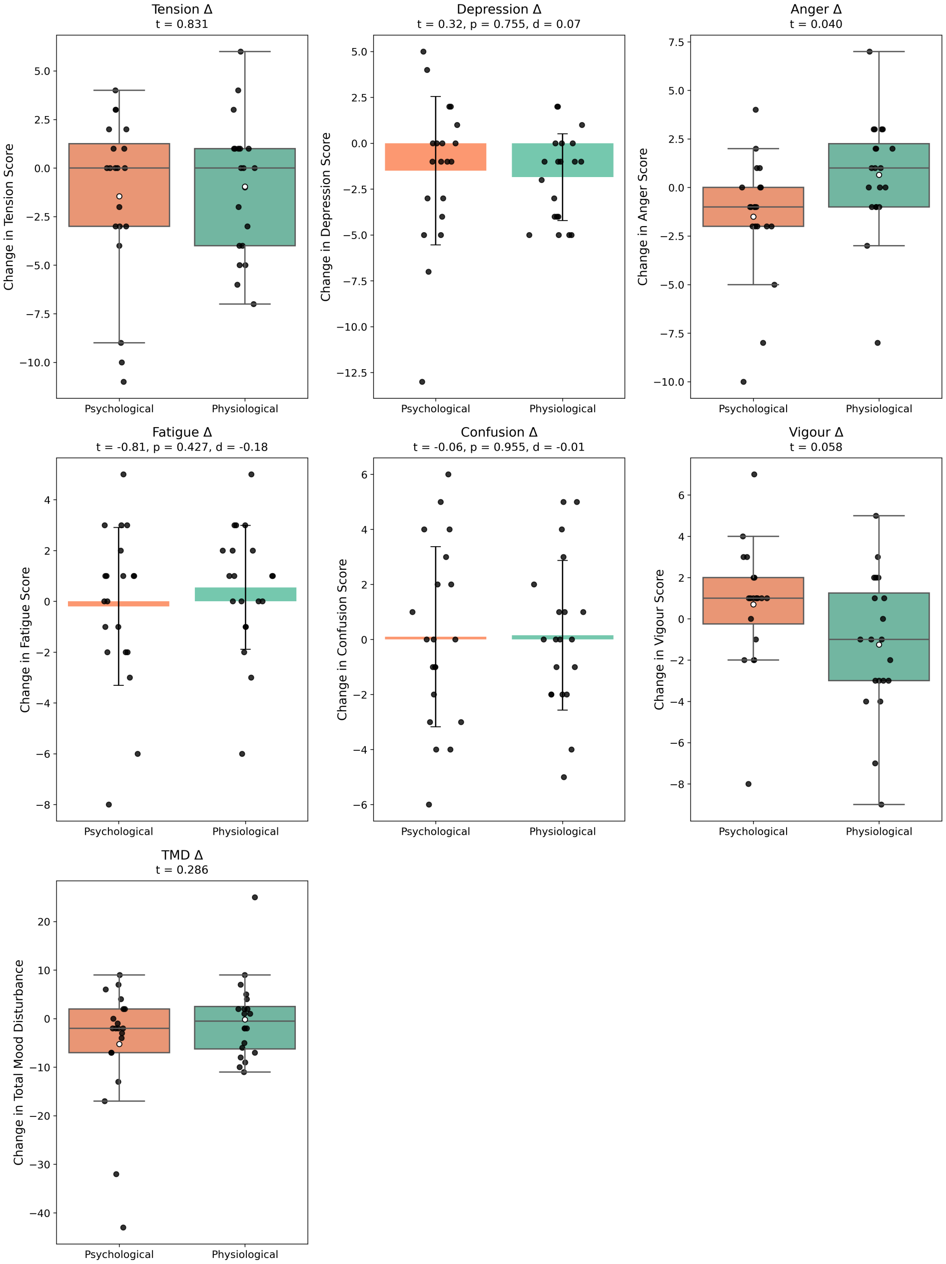

Figure 4.2: Changes in POMS mood subscales (Δ = Post − Pre) after "Psychological" and "Physiological" HIIT: Tension, Depression, Anger, Fatigue, Confusion, Vigour, and total mood disturbance (TMD). Panels report the specific test used (paired *t*-test or Wilcoxon signed-rank) based on Shapiro–Wilk. Black dots show paired participants; white circles are means; boxes show median and IQR (or bars = mean ± SD for *t*-test panels).

Table 4.2: Mean ± SD changes (Δ = POST – PRE) in Profile of Mood States (POMS) subscales for "Psychological" and "Physiological" HIIT sessions. Negative values indicate reductions in mood states from pre- to post-exercise. *$p < 0.05$ compared to Physiological HIIT mean.

	Psychological HIIT		Physiological HIIT	
Measure	Mean	SD	Mean	SD
Δ Tension	-1.45	4.30	-0.95	3.47
Δ Depression	-1.50	4.05	-1.85	2.37
Δ Anger	-1.50*	3.17	0.65	2.98
Δ Fatigue	-0.20	3.11	0.55	2.44
Δ Confusion	0.10	3.28	0.15	2.72
Δ Vigour	0.70	2.96	-1.25	3.42
Δ TMD	-5.25	12.79	-0.20	8.26

higher during the "Psychological" HIIT ($p = 0.009$), while anger was significantly lower ($p = 0.040$), indicating a more positive affect experience. No significant differences were found for RPE, Feeling Scale, or other mood dimensions (depression, tension, fatigue, confusion, vigor).

4.3 Theta Band Analysis

Figure 4.3 highlights the difference between the "Psychological" and "Physiological" HIIT sessions (PS – PH), indicating that theta power was significantly higher following the "Psychological" HIIT than the "Physiological" HIIT, particularly over frontal and central regions.
Overall, theta power differed between the two HIIT protocols: "Psychological" HIIT showed larger post-exercise theta increases than "Physiological" HIIT at several frontal and central electrodes

4.4 Alpha Band Analysis

Based on Figure 4.4, the "Psychological" HIIT session showed a greater increase in alpha power compared to the "Physiological" HIIT session, particularly over frontal and temporal regions; however, this effect was not as pronounced as that observed for theta power (i.e., fewer electrodes showed significant differences, see Table 4.4).

In summary, alpha power changes distinguished the two HIIT conditions: "Psychological" HIIT produced greater frontal–temporal alpha enhancement (typically

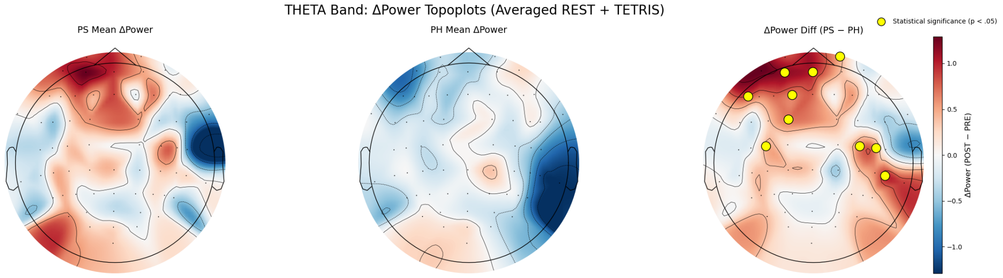

Figure 4.3: Scalp topographies of theta (4–7 Hz) power change (ΔPower = POST − PRE), averaged across REST and Tetris. Left: Psychological HIIT (PS); middle: Physiological HIIT (PH); right: difference (PS − PH). Warmer colors indicate increased post-exercise theta power and cooler colors indicate decreases; marked electrodes indicate significant PS–PH differences ($p < 0.05$).

Table 4.3: Significant electrodes showing theta band changes (POST – PRE) in the "Psychological" HIIT session compared to the "Physiological" HIIT session. Paired-sample tests revealed significant differences across several electrodes. The test type (paired t-test or Wilcoxon signed-rank test) was selected based on Shapiro–Wilk normality results.

Electrode	p-value	Test Type
AF3	0.023	Wilcoxon
AFz	0.030	Paired t-test
F1	0.048	Wilcoxon
F7	0.040	Wilcoxon
FC1	0.007	Paired t-test
C3	0.044	Wilcoxon
C4	0.017	Wilcoxon
C6	0.025	Wilcoxon
FP2	0.044	Wilcoxon
TP8	0.019	Wilcoxon

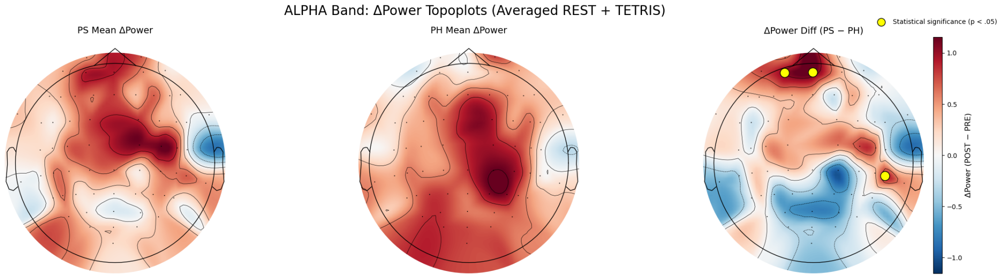

Figure 4.4: Significant electrodes showing theta band changes (POST – PRE) in the "Psychological" HIIT session compared to the "Physiological" HIIT session. Paired-sample tests revealed significant differences across several electrodes. The test type (paired t-test or Wilcoxon signed-rank test) was selected based on Shapiro–Wilk normality results. (see Table 4.3)

Table 4.4: Significant electrodes showing alpha band changes (POST – PRE) in the "Psychological" HIIT session compared to the "Physiological" HIIT session. Paired-sample tests revealed significant changes in several electrodes. The test type (paired t-test or Wilcoxon signed-rank test) was selected based on Shapiro–Wilk normality results.

Electrode	**p-value**	**Test Type**
AF3	0.016	Paired t-test
AFz	0.007	Paired t-test
TP8	0.023	Wilcoxon

linked to positive affect) compared to "Physiological" HIIT; however, this effect was limited to three electrodes.

4.5 Beta Band Analysis

Figure 4.5 outlines the difference between the "Psychological" and "Physiological" HIIT sessions (PS – PH), indicating that beta power was significantly higher following the "Psychological" HIIT than the "Physiological" HIIT, particularly over frontal regions. Similar to the alpha band, fewer electrodes showed significant differences compared to the theta band. (see Table 4.5)

Overall, beta power changes differentiated the two HIIT conditions, with "Psychological" HIIT showing significant effects in four frontal electrodes, suggesting stronger frontal beta activity (i.e., greater cortical activation and engagement) compared to "Physiological" HIIT.

All EEG inferential comparisons were performed on change scores (ΔPower =

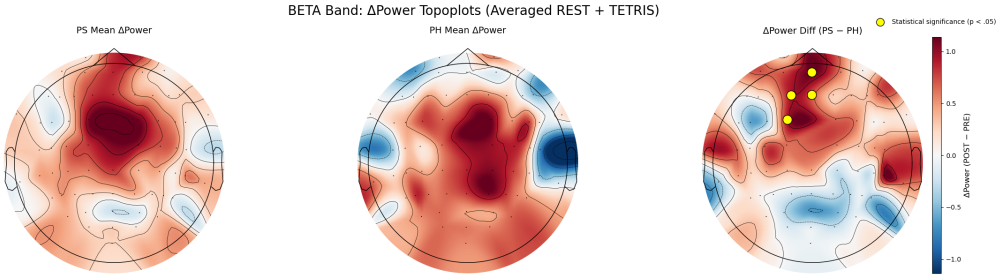

Figure 4.5: Scalp topographies of beta (13–30 Hz) power change (ΔPower = POST − PRE), averaged across REST and Tetris. Left: Psychological HIIT (PS); middle: Physiological HIIT (PH); right: difference (PS − PH). Warmer colors indicate increased post-exercise beta power and cooler colors indicate decreases; marked electrodes indicate significant PS–PH differences ($p < 0.05$).

Table 4.5: Significant electrodes showing beta band changes (POST – PRE) in the "Psychological" HIIT session compared to the "Physiological" HIIT session.

Electrode	***p*-value**	**Test Type**
AFz	0.012	Wilcoxon
F1	0.008	Wilcoxon
FC1	0.021	Wilcoxon
Fz	0.040	Wilcoxon

POST − PRE) rather than on POST values alone. This approach was selected because the primary aim was to quantify protocol-related differences in post-exercise change while accounting for stable individual differences in scalp power and any day-to-day variability between sessions. Using ΔPower also aligns with the within-subject crossover design, where each participant serves as their own baseline within each condition. For visualization, Figures 4.3– 4.5 display the mean ΔPower topographies for each protocol and the PS–PH difference map; the underlying PRE and POST power values are not shown separately to keep figures compact and to emphasize the main inferential target (protocol differences in pre-to-post change). For completeness, future versions could include supplementary PRE and POST topographies; however, the statistical conclusions in the present thesis are based on ΔPower as defined above.

4.6 Frontal Asymmetry Analysis

Frontal asymmetry (FA), computed as the difference in power between homologous right and left frontal electrode pairs (e.g., F4 – F3, AF4 – AF3), was examined for the theta, alpha, and beta bands. The FA index was averaged across all predefined

Table 4.6: Statistical comparison of frontal asymmetry (FA) indices across theta, alpha, and beta bands. The table reports paired-sample p-values for within-condition changes (Post–Pre) in "Psychological" (PS) and "Physiological" (PH) HIIT protocols, as well as between-condition comparisons (PS vs. PH) for each state (Rest and Tetris). A significant effect ($p < 0.05$) was observed for theta asymmetry during the Tetris state. The interpretation of this significant difference is further explained in Figure 4.9

Band	**State**	**p-value PS (Post–Pre)**	**p-value PH (Post–Pre)**	**p-value PS vs. PH**
θ	Rest	0.464	0.394	0.821
θ	Tetris	0.372	0.030*	0.030*
θ	Average (Rest+Tetris)	—	—	0.057
α	Rest	0.508	0.271	0.691
α	Tetris	0.782	0.156	0.332
α	Average (Rest+Tetris)	—	—	0.362
β	Rest	0.085	0.948	0.190
β	Tetris	0.810	0.697	0.709
β	Average (Rest+Tetris)	—	—	0.856

frontal pairs for each participant, condition, and state (Rest, Tetris), and compared across timepoints (POST – PRE) and protocols ("Psychological" vs. "Physiological" HIIT). Table 4.6 summarizes the resulting p-values from paired t-tests or Wilcoxon signed-rank tests, depending on normality (see Figure 4.6).

Overall, no significant PRE–POST changes in frontal asymmetry were detected within the "Psychological" HIIT (PS) condition across any frequency band. In contrast, a significant effect emerged in the theta band during the "Physiological" HIIT (PH) protocol under the Tetris condition ($p = 0.03$), and this difference was also significant when directly comparing the two protocols ($p = 0.03$). The frontal theta asymmetry results during Tetris reveal a meaningful neural difference between the HIIT formats: PS produced a left-dominant increase in theta power (Right – Left ≈ -0.42), a pattern typically associated with enhanced cognitive readiness, greater task engagement, and a more adaptive affect state. Conversely, PH elicited a right-dominant increase in theta power ($\approx +0.46$), which is commonly linked to heightened cognitive strain, reduced regulatory efficiency, or greater perceived fatigue. Together, these findings suggest that the psychologically structured HIIT protocol supports a more favorable post-exercise emotional state compared to the physiologically prescribed protocol.

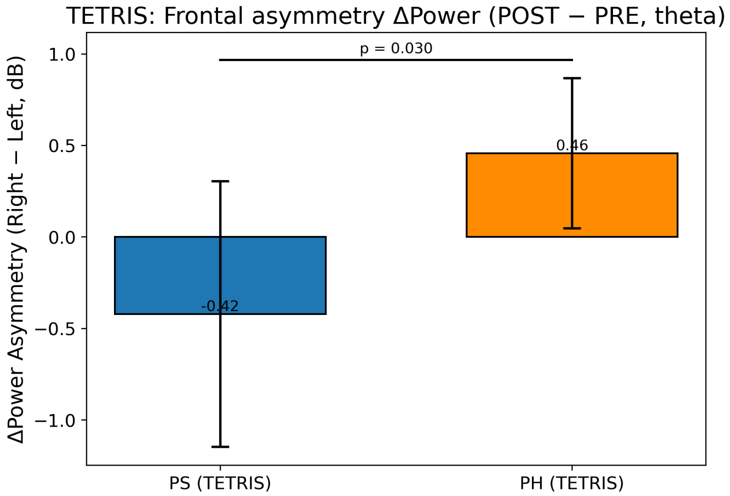

Figure 4.6: Frontal theta (4–8 Hz) asymmetry change during Tetris (ΔPower = POST − PRE; Right − Left across frontal pairs) for Psychological (PS) and Physiological (PH) HIIT. Bars show mean ± SEM; the between-protocol comparison is annotated ($p = 0.030$).

4.6.1 Theta Band Correlations

Correlational analyses were performed to explore associations between theta power changes (ΔPower = POST − PRE; averaged across significant electrodes) and perceptual measures across the "Psychological" (PS) and "Physiological" (PH) HIIT sessions. Within the "Physiological" condition, greater theta power increases were significantly associated with reductions in total mood disturbance (TMD; $r = -0.46$, $p = 0.040$) and tension ($r = -0.51$, $p = 0.020$), suggesting that enhanced theta activity after exercise was linked to more positive mood states. A marginal positive trend was also observed between theta power and self-reported pleasure (Feeling Scale; $r = 0.44$, $p = 0.054$). In contrast, no significant associations were found in the "Psychological" protocol.

4.6.2 Alpha Band Correlations

Correlational analyses examined the relationships between alpha power changes (ΔPower = POST − PRE; averaged across significant electrodes) and perceptual variables across both HIIT sessions (Figure4.7). The "Physiological" HIIT session showed a more consistent pattern of negative relationships between ΔAlpha power and mood disturbance indicators. In particular, higher post-exercise alpha power was marginally related to lower scores in tension ($r = -0.42$, $p = 0.068$) and anger ($r = -0.40$, $p = 0.082$). Overall, most correlations in the "Physiological" HIIT condition were weak and non-significant. In "Psychological" HIIT, correlations were weaker, less consistent, and non-significant across all cases (see Figure‘4.8).

4.6.3 Beta Band Correlations

Correlations between beta (13–30 Hz) power changes (ΔPower = POST – PRE; averaged across significant electrodes) and behavioral or affective variables showed that, among all frequency bands, beta exhibited the strongest association, with a significant positive correlation between ΔBeta power and enjoyment ($r = 0.61$, $p = 0.005$) during the “Psychological” HIIT protocol. This suggests that greater increases in beta activity were linked to higher reported enjoyment, potentially reflecting enhanced cortical activation and affective engagement. In contrast, correlations in the “Physiological” HIIT protocol were weak and non-significant, with small negative or near-zero associations across most affective measures, indicating limited coupling between beta modulation and perceptual responses. Overall, higher beta power during “Psychological” HIIT may reflect greater alertness and engagement; however, these findings should be interpreted with caution, as this was the only significant correlation observed.

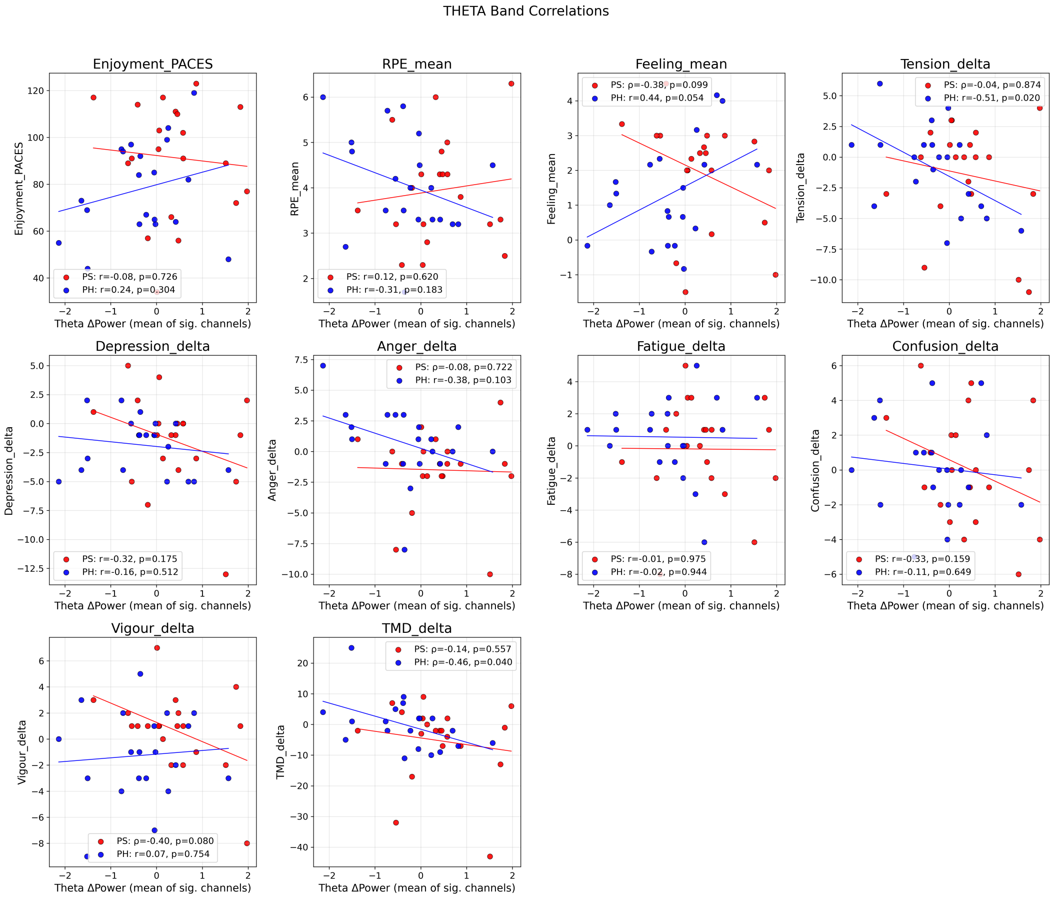

Figure 4.7: Correlations between mean theta ΔPower (POST – PRE; averaged across significant electrodes for both HIIT protocols and across the Rest and Tetris conditions) and behavioral or affective variables for "Psychological" (red) and "Physiological" (blue) HIIT protocols. Data points represent individual participants, with regression lines shown for each condition. Correlation coefficients are displayed as r for normally distributed data (Pearson's correlation) and ρ for non-normal data (Spearman's correlation), along with their corresponding p-values.

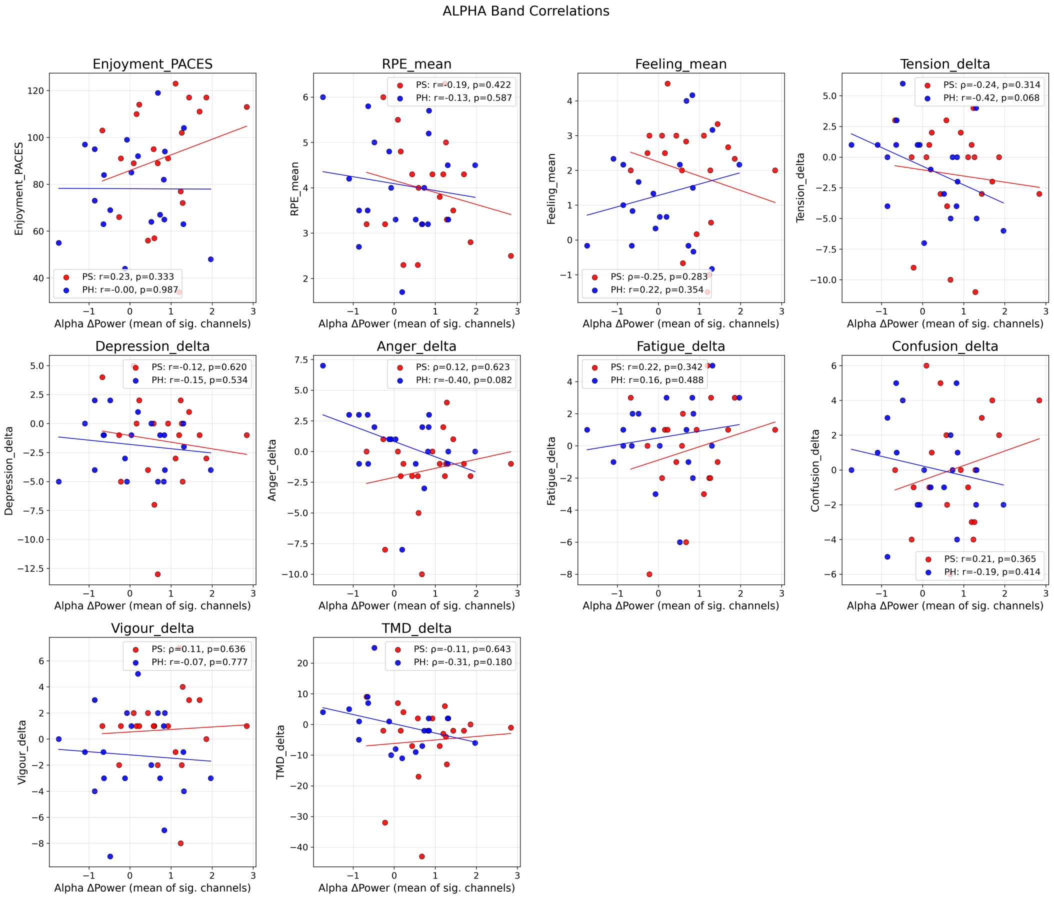

Figure 4.8: Correlations between mean alpha ΔPower (POST – PRE; averaged across significant electrodes) and perceptual variables for "Psychological" (red) and "Physiological" (blue) HIIT sessions. Points represent participants, with regression lines for each condition. Correlation coefficients are reported as r (Pearson) or ρ (Spearman), with corresponding p-values.

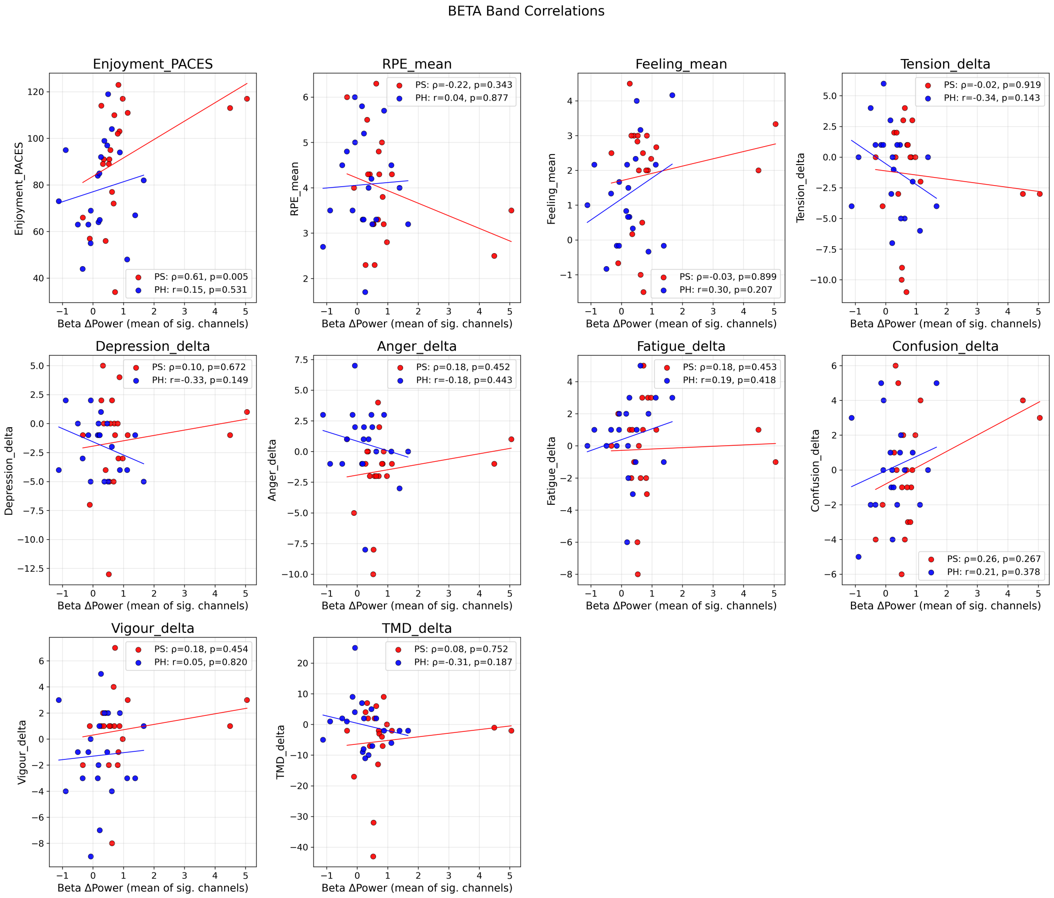

Figure 4.9: Correlations between mean alpha ΔPower (POST–PRE; averaged across significant electrodes) and perceptual variables for "Psychological" (red) and "Physiological" (blue) HIIT sessions. Points represent participants with regression lines for each condition. Correlations are reported as r (Pearson) or ρ (Spearman) with corresponding p-values.

Chapter 5

Discussion

This thesis investigated how two types of high-intensity interval training (HIIT) protocols—"Psychological" HIIT with fixed bout durations and "Physiological" HIIT with individualized bout durations (i.e., based on the individual's time limit at MAS)—influence EEG oscillations and affect responses in untrained female participants. The overarching research question examined whether these two HIIT formats, which differ primarily in their interval structure, elicit different neural recovery patterns and post-exercise affect responses. To address this question, three objectives were pursued: (1) to examine the effects of each HIIT protocol on enjoyment, perceived exertion, affective valence, and mood; (2) to compare post-exercise changes in EEG theta, alpha, and beta power (including frontal asymmetry) between the two protocols; and (3) to investigate the relationships between EEG changes and these perceptual and affective measures to provide an integrated understanding of how neural activity and psychological responses co-vary following HIIT.

Regarding the first objective, perceptual and affective measures revealed consistent patterns across both protocols. Perceived exertion was comparable between conditions (RPE = 3.94 ± 1.16 vs. 4.07 ± 1.12; $p = 0.67$), confirming similar workload. However, enjoyment (PACES) was higher following the "Psychological" HIIT (91.35 ± 24.33 vs. 78.10 ± 20.04; $p = 0.009$, $d = 0.65$), and Feeling scores were more positive (1.91 ± 1.58 vs. 1.33 ± 1.42; $p = 0.070$). POMS subscales showed small-to-moderate improvements, including a significant reduction in Anger ($\Delta = -1.50 \pm 3.17$; $p = 0.040$) and a trend toward increased Vigour ($\Delta = 0.70 \pm 2.96$; $p = 0.058$). These findings suggest that although both protocols imposed comparable physiological effort, the fixed and shorter bouts and the pattern of the "Psychological" HIIT likely contributed to higher enjoyment and more positive mood.

The second objective focused on EEG dynamics following exercise. Post-exercise increases in theta, alpha, and beta power were observed in the "Psychological" HIIT condition compared to the "Physiological" HIIT. Theta power increased across frontal and central sites (e.g., AF3, AFz, FC1, C4). Alpha power also increased, with the strongest changes seen over frontal and temporal regions (AF3, AFz, TP8). Beta power showed post-exercise increases at frontal and fronto-central electrodes including AFz, F1, FC1, and Fz. No asymmetry effects were detected in the alpha or beta bands; however, a theta-band asymmetry emerged during the Tetris condition, driven by a right-frontal shift following the "Physiological" HIIT protocol ($p = 0.030$) and a corresponding difference between the two protocols. Overall, these results indicate that the "Psychological" HIIT protocol produced greater post-exercise oscillatory changes across multiple frequency bands, particularly within frontal and central regions.

The third objective examined correlations between EEG and perceptual measures. Although most correlations were not significant and inconsistent, a few meaningful patterns emerged. In the "Psychological" condition, beta power change positively correlated with enjoyment ($r = 0.61$, $p = 0.005$), suggesting that greater beta enhancement corresponds to a more positive affect response. In the "Physiological" condition, theta power was negatively correlated with total mood disturbance ($r = -0.46$, $p = 0.040$) and tension ($r = -0.52$, $p = 0.020$), consistent with the role of theta in affect regulation. Weak negative trends between alpha power and anger or tension ($r \approx -0.4$) also suggested links with emotional stability; however, these results should be interpreted with caution. Although preliminary and inconsistent, these relationships point toward possible connections between neural activity and affective experience following HIIT.

5.0.1 Perceptual Responses

Our findings on participants' post-exercise experiences align with evidence that a single exercise session can improve mood and reduce negative affect responses such as anxiety and fatigue [103]. Work in exercise psychology indicates that affect responses during exercise influence future exercise behavior and are shaped by the structure of the workout [31, 32].

Research comparing interval formats shows that shorter work intervals, as opposed to longer or time-to-exhaustion bouts, are often associated with higher enjoyment and lower perceived exertion, even when overall workload is similar [6, 12, 73]. A comparable pattern emerged in our study. Although the "Psychological" and "Physiological" HIIT protocols elicited similar levels of perceived exertion (RPE), the "Psychological" HIIT produced higher enjoyment (PACES) and a more positive mood response in the anger dimension.

Evidence from the HIIT literature shows that high-intensity exercise does not necessarily lead to negative affect when it is performed in intervals, as recovery periods support more positive affect responses [57]. Short, near-maximal intervals of approximately 60 seconds have been shown to elicit affect responses comparable to continuous moderate-intensity exercise and more positive than continuous vigorous exercise across inactive and clinical populations [5, 47, 57]. Research on perceived exertion further indicates that shorter intervals are experienced as less demanding than longer intervals or continuous exercise, even when total workload is matched. Longer intervals (e.g., 2 minutes) tend to feel more difficult, partly because anticipating a sustained effort increases discomfort [58]. Supporting this interpretation, studies on mental fatigue demonstrate that increased cognitive effort elevates perceived exertion and reduces endurance performance without changes in muscle function, highlighting the importance of cognitive recovery during high-intensity exercise [65, 75].

Consistent with these findings, Olney et al. reported higher enjoyment (PACES) during low-volume HIIT compared with high-volume HIIT in women, despite greater physiological stress in the higher-volume condition [74]. Martinez et al. also showed that HIIT protocols with shorter intervals (e.g., 60 seconds) were associated with higher post-exercise enjoyment than longer intervals (e.g., 120 seconds), with enjoyment declining primarily in the longest-interval and continuous exercise conditions [66]. Together, these results suggest that shorter and lower-volume HIIT sessions may be perceived as more enjoyable and less demanding, underscoring the importance of interval duration and structure in shaping affect and perceptual responses to high-intensity exercise.

Within this context, the structured and time-limited design of the "Psychological" HIIT protocol in the present study may have supported a more positive perceptual experience despite similar physical demands across protocols.

5.0.2 EEG Responses

The second objective of this thesis was to compare neurophysiological responses across the two HIIT protocols, focusing on post-exercise changes in theta, alpha, and beta power and on frontal asymmetry. EEG is appropriate for this purpose because it offers a physiological complement to self-report affective measures and allows examination of exercise-related changes in cortical activity [14]. In exercise research, EEG has been used to study fluctuations in brain rhythms related to emotional, cognitive, and attentional states [27, 30], and both acute and short-term exercise have been shown to influence oscillatory activity across several frequency bands [45].

Early investigations often reported increases in alpha power following aerobic exercise [78]. Youngstedt [104] observed decreased theta, increased alpha, and increased beta, indicating a shift toward faster activity and higher cortical activation. These varied findings highlight the need to examine multiple frequency bands. Accordingly, the present study assessed changes in theta, alpha, and beta power across both HIIT protocols to characterize exercise-related neural responses and to explore their association with affective and cognitive outcomes [61].

Research in affective neuroscience indicates that anterior hemispheric asymmetry can serve as an index of affective tendencies. Reduced alpha power over the left frontal hemisphere (greater left activation) has been linked to positive affect and approach-oriented tendencies, whereas reduced alpha over the right hemisphere (greater right activation) has been associated with negative affect and withdrawal tendencies [14, 91]. As affect responses influence exercise adherence, frontal asymmetry provides a useful framework for interpreting neural patterns observed after exercise.

In this study, the "Psychological" HIIT protocol produced larger post-exercise increases in theta, alpha, and beta power than the "Physiological" HIIT protocol, with effects most apparent over frontal and central regions. These changes may reflect differences in cortical engagement or recovery processes. Frontal theta is particularly relevant in this context because it has been associated with cognitive control, performance monitoring, and emotion-regulation processes [13, 21, 76, 95]. Although alpha and beta asymmetry did not differ between protocols, a difference emerged in the theta band during the post-exercise Tetris phase. The "Physiological" HIIT protocol showed a right-dominant theta pattern, whereas the "Psychological" HIIT protocol showed a left-dominant theta pattern.

In the present dataset, post-exercise power changes tended to be larger in the Psychological HIIT condition than in the Physiological HIIT condition at several frontal (and fronto-central) electrodes across theta, alpha, and beta bands. This pattern may reflect differences in how the two interval prescriptions were experienced or regulated (e.g., predictability of bout duration, cognitive effort, or recovery demands), but it should be interpreted cautiously because the electrode-wise effects were not robust to multiple-comparison correction and substantial inter-individual variability was observed. Accordingly, we treat this frontal pattern as a consistent descriptive trend that motivates replication with larger samples and more targeted region-of-interest analyses to determine whether it represents a reliable protocol-related difference.

The stronger frontal–central theta increases observed after the Psychological HIIT protocol may reflect differences in post-exercise cognitive or regulatory demands between protocols. Frontal–central theta has been discussed in the literature as an index related to cognitive control and monitoring processes, and in the present study this pattern was most apparent over fronto-central sites. Given the exploratory nature of the electrode-wise findings, this interpretation is offered cautiously. Baseline predictors of mood change were not a primary objective of the present study and were therefore not formally tested. In the current analyses, baseline (pre-exercise) measures were used to compute within-session change scores (POST − PRE) for each mood outcome, and comparisons focused on differences in these change scores between the Psychological and Physiological HIIT conditions. As a result, we cannot conclude from the planned analyses whether baseline mood or baseline EEG features predicted subsequent mood changes in either condition;

Rationale for within-condition analyses The primary statistical focus of this thesis was the within-subject comparison between protocols (Psychological vs. Physiological), and for EEG band power this was implemented by comparing pre-to-post change scores (ΔPower = POST − PRE) between conditions. This approach directly tests whether the two protocols differ in the magnitude of post-exercise change while controlling for stable individual differences in baseline power. For questionnaires, the availability of baseline measurements differs by instrument: POMS was collected both pre- and post-session and is therefore reported as Δ (POST − PRE), whereas PACES was administered only after each session and RPE/Feeling Scale were recorded during the session (and summarized as session-level values), so pre–post testing is not applicable for those measures. Frontal asymmetry was additionally examined within each condition (PRE vs. POST) because it is a derived left–right index and testing within-condition change provides a direct check of whether each protocol produced a hemispheric shift relative to baseline. Within-condition PRE–POST tests for band power can be added as supplementary analyses; however, they were not emphasized because the main inferential question concerned between-protocol differences in pre-to-post change.

Taken together, these findings suggest that the “Psychological” HIIT protocol may influence post-exercise neural patterns differently than the “Physiological” HIIT protocol.

5.0.3 EEG–Behavior Correlations

The primary purpose of the present study was to investigate whether changes in EEG activity are related to perceptual and affect responses following HIIT, providing an integrated understanding of how neural and psychological processes co-vary after exercise. Previous research by Petruzzello and colleagues [78] has shown that pre-exercise resting levels of frontal alpha asymmetry were moderately associated with pre- to post-exercise improvements in mood, specifically decreases in anxiety and increases in energetic arousal. Their findings also indicated that reductions in anxiety following exercise were related to changes in alpha asymmetry, although their later study did not replicate this association [79].

Only a limited number of studies have examined how exercise duration influences affect responses, but existing evidence suggests that duration may follow a threshold pattern—producing affective benefits up to a certain point, after which valence may deteriorate [35, 101]. In the context of the present HIIT protocols, our results showed that theta power in the “Physiological” condition was related to tension, while beta power in the “Psychological” condition was associated with increased vigour and greater enjoyment, and alpha changes showed associations with anger. To our knowledge, no previous study has specifically investigated EEG–affect correlations in HIIT exercise, making the current findings an initial step toward understanding how high-intensity interval exercise shapes the interplay between neural activity and affective experience.

5.0.4 Strengths and Limitations

One of the main strengths of this study is its within-subjects crossover design, meaning that every participant completed both the “Psychological” and “Physiological” HIIT sessions. This helped reduce natural inter-individual variability, making it easier to identify differences attributable to the protocols themselves. Another strength is that the order of the HIIT sessions was randomized, and participants were not informed of the protocol order across participants. This reduced the risk of bias or preconceived expectations influencing their experience or responses. In addition, the exercise sessions were individualized based on each participant’s maximal aerobic speed (MAS) and time limit at MAS, ensuring that both protocols were tailored to individual fitness levels and improving the accuracy of between-condition comparisons.

Despite these strengths, the study also has important limitations. First, the sample size was relatively small, particularly for EEG analyses in the context of HIIT exercise, which remains largely unexplored. With fewer participants, individual differences or outlier responses can exert a stronger influence on group-level results, although efforts were made to mitigate these effects. A larger sample size would likely reduce the impact of variability and improve statistical robustness. Second, the study examined only acute, post-exercise effects. Chronic or long-term training adaptations were not assessed, and EEG and behavioral responses may differ following repeated exposure over weeks or months. As a result, the findings cannot be generalized to long-term adaptations. Finally, the study focused exclusively on untrained female participants, limiting the generalizability of the results to other populations, such as trained individuals or male participants.

5.0.5 Interpretation and Implications of the Findings as a Whole

When considered together, the perceptual and EEG results suggest that interval structure may shape the post-exercise experience even when perceived effort is similar. In this sample, the fixed-bout protocol was associated with higher enjoyment and a more favorable change in the anger subscale, while also showing larger post-exercise oscillatory changes (theta/alpha/beta) in frontal–central regions. A cautious interpretation is that shorter, predictable bouts may reduce the psychological burden of sustained high-intensity effort (e.g., less uncertainty about how long a bout will last) and may support a more positive immediate experience of HIIT. In parallel, the observed EEG patterns (including stronger frontal–central theta in PS and a protocol-related theta asymmetry during the post-exercise cognitive task) may reflect differences in post-exercise cognitive-emotional regulation, engagement, or recovery. Importantly, because most correlations were exploratory and electrode-wise effects did not survive strict correction, these EEG findings should be interpreted as candidate mechanisms rather than definitive neural markers. Nonetheless, the convergence of higher enjoyment with protocol-related EEG differences supports the broader conclusion that "how HIIT is structured" can matter for both affective experience and measurable brain dynamics following exercise.

From a sports science perspective, the combined perceptual and EEG results are consistent with the practical view that interval structure can shape the immediate exercise experience even when perceived exertion is similar. In this sample, the fixed-bout (Psychological) protocol was associated with higher enjoyment and a more favorable anger response, alongside larger post-exercise oscillatory changes over frontal–central regions. A conservative interpretation is that shorter, predictable bouts may reduce the psychological cost of sustaining near-maximal effort (e.g., reduced uncertainty about bout duration) and may support a more positive affective response in untrained participants. From a computer science perspective, the study also demonstrates that reproducible signal-processing workflows can translate noisy, high-dimensional EEG recordings into interpretable features (band-limited power and asymmetry indices) that can be aligned with behavioral outcomes. In particular, the convergence of protocol-related differences across multiple bands and frontal electrodes suggests that feature engineering choices (e.g., PSD estimation approach, artifact correction, and pre/post change scoring) may meaningfully influence the sensitivity of EEG markers to exercise manipulations. While these findings should be interpreted cautiously given the exploratory nature of electrode-wise effects and the limited sample size, they collectively support the broader conclusion that protocol design and analytical pipeline decisions both contribute to what can be detected about post-exercise brain dynamics and affective experience.

5.0.6 Generalizability and Hormone-Related Considerations

A key limitation of this study is that it was conducted only in untrained female participants, so the findings may not generalize to males, trained individuals, or other populations. It is possible that sex-related physiological differences could influence both affective responses to HIIT and post-exercise EEG patterns, meaning that the direction or magnitude of effects may differ in men. In addition, although menstrual-cycle factors were considered during screening, the study was not designed or powered to test cycle-phase effects, and hormonal status (e.g., cycle phase, hormonal contraception use, or endocrine conditions such as PCOS) was not systematically controlled, recorded, or modeled. As a result, potential hormone-related influences on mood, perceived exertion, and neural responses may have been missed or may have contributed to unexplained variability. Future studies should include male participants and prospectively track hormonal factors to evaluate whether protocol-related effects differ across sex and hormonal profiles.

5.0.7 Practical Use of the Findings

From an applied perspective, the results provide a practical hypothesis for exercise prescription in untrained populations: when the goal is to encourage adherence and maintain positive engagement, a fixed-bout HIIT format with short, predictable intervals may be a reasonable starting point. In community or coaching settings, a protocol that participants perceive as more enjoyable can be used to reduce early dropout, improve confidence, and support repeated participation—even if both protocols are physiologically demanding. Practitioners could implement this by beginning with short intervals (e.g., around 60 seconds) and gradually adjusting interval number or intensity as tolerance improves, while monitoring enjoyment, RPE, and affective valence. Although EEG measures are not typically available in applied settings, the current findings support the idea that affective reports (PACES, Feeling Scale, mood subscales) can serve as meaningful indicators of how a protocol is being experienced and may help guide individualized progression.

In terms of recommendations, an applied sports science interpretation is that fixed, short-interval HIIT may be a reasonable entry-point for untrained individuals when the goal is to promote adherence through a more positive subjective experience, provided that intensity and progression are managed responsibly. Based on expert judgment in exercise prescription, practitioners could prioritize interval structures that are easy to understand and anticipate (e.g., short work bouts with clear recovery), monitor enjoyment and affective valence alongside RPE, and adjust volume gradually to maintain tolerability while preserving the intended training stimulus. From an analytics and computer science standpoint, the results motivate practical recommendations for future EEG-based exercise studies and potential monitoring applications: (i) prioritize standardized preprocessing and artifact correction to reduce non-neural variance, (ii) report PSD estimation choices transparently to support reproducibility, and (iii) use within-subject change metrics (POST − PRE) when the aim is to isolate intervention-related effects from stable individual differences. If replicated, the combination of brief self-report measures and robust EEG feature extraction could support more individualized exercise programming by identifying protocol formats that better align with positive affect and recovery-related neural signatures in specific subgroups.

5.0.8 Novelty and Next Steps

The present work is novel in that it combines a within-subject crossover comparison of two HIIT prescriptions with post-exercise EEG outcomes and multiple affective/perceptual measures, allowing protocol effects to be examined while reducing inter-individual variability. It also introduces an analysis strategy that evaluates EEG changes both in a resting context and during a standardized cognitive engagement period, providing complementary windows into post-exercise brain dynamics. Building on these findings, several next steps are recommended.

First, replication with larger samples is needed to evaluate the stability of the electrode-wise patterns and to support stronger statistical correction. Second, future studies should explicitly record and model menstrual cycle phase, hormonal contraceptive use, and cycle-related conditions (e.g., PCOS), and should include male participants to test sex-related generalizability. Third, studies could extend beyond acute responses to examine whether affective preference and EEG recovery patterns predict adherence over weeks of training. Finally, incorporating more targeted neural outcomes (e.g., predefined regions of interest, or task-evoked EEG features during cognitive control paradigms) may help clarify whether the observed theta/alpha/beta changes reflect regulation, fatigue, or motivational engagement after different HIIT prescriptions.

Chapter 6

Conclusions

This thesis investigated whether two high-intensity interval training (HIIT) prescriptions—a fixed-bout "Psychological" protocol and an individualized-bout "Physiological" protocol based on time limit at maximal aerobic speed (t_{lim} at MAS)—are associated with different affective responses and post-exercise EEG dynamics in untrained female participants. By integrating standardized self-report measures (PACES, RPE, Feeling Scale, and POMS) with pre/post EEG recordings collected during resting and cognitive-task states, the work provides an initial multimodal characterization of how interval structure may shape both subjective experience and measurable neural responses following HIIT.

Main contributions and advantages of the approach: The first contribution is an experimental comparison of two practically relevant HIIT designs under a within-subject crossover framework, which reduces inter-individual variability and supports more direct protocol-level inference. The second contribution is the development of a reproducible analysis workflow that translates high-dimensional EEG recordings into interpretable oscillatory features (theta, alpha, and beta band power and frontal asymmetry) and links these features to affective and perceptual outcomes using transparent statistical decision rules. A key advantage of this combined approach is that it complements subjective reports with objective neural indices, enabling future work to test candidate mechanisms through which protocol structure could influence engagement, recovery, and adherence-related outcomes.

Summary of key findings: Across protocols, perceived exertion (RPE) was similar, suggesting comparable subjective intensity. However, the "Psychological" HIIT protocol produced higher enjoyment (PACES) and a more favorable change in the anger mood subscale, while other mood dimensions showed no clear between-protocol differences. In the EEG results, post-exercise power changes tended to be larger following "Psychological" HIIT than "Physiological" HIIT across theta, alpha, and beta bands at several frontal and fronto-central electrodes. No clear alpha- or beta-asymmetry effects were observed, while a theta-band asymmetry difference emerged during the post-exercise cognitive task. EEG–behavior associations were limited and should be interpreted cautiously; nevertheless, beta changes showed a positive association with enjoyment in the Psychological condition, and theta changes were associated with reductions in mood disturbance and tension in the Physiological condition.

Strengths and limitations: Strengths of this study include the within-subject crossover design, standardized pre/post EEG recordings under two states (rest and task), and the use of validated affective instruments alongside a transparent EEG processing and statistical workflow. Important limitations include the modest sample size and the exploratory nature of electrode-wise EEG findings, which were not robust under strict multiple-comparison control. In addition, the study focused on acute responses and on untrained female participants; generalizability to males, trained individuals, and different hormonal profiles (e.g., menstrual cycle phase, hormonal contraception, endocrine conditions) remains uncertain. Finally, because not all questionnaires were collected both pre and post (e.g., PACES is post-only), not all outcomes can be analyzed using within-session change scores.

Societal, health, and practical implications: From a public health and exercise-adherence perspective, the results support the practical hypothesis that fixed, short, and predictable HIIT intervals may be better tolerated and more enjoyable for untrained individuals, which could be relevant when designing programs intended to increase physical activity participation. Although EEG is not routinely available in applied settings, the present findings reinforce the value of combining simple self-report measures (enjoyment, perceived exertion, affective valence, and mood) with structured training design to improve early engagement and reduce dropout risk. From a broader methodological perspective, the proposed workflow illustrates how computer science tools for signal processing, feature extraction, and reproducible analysis can help quantify neurophysiological responses to exercise and generate testable hypotheses about brain–behavior relationships during recovery.

Recommendations for future work: Future studies should (i) replicate these findings in larger samples to improve statistical power and enable stricter multiple-comparison control; (ii) test generalizability by including male participants, trained participants, and prospectively tracking hormonal status (cycle phase, contraception use, and endocrine conditions); (iii) extend beyond acute designs to determine whether protocol-specific affective and EEG patterns predict adherence and training response over weeks of repeated HIIT exposure; and (iv) refine neural outcomes by using predefined regions of interest, task-evoked EEG markers, and complementary physiological measures (e.g., HRV) to better characterize recovery dynamics. Multimodal designs that combine EEG-derived features with practical coaching variables may ultimately support more individualized HIIT prescriptions that prioritize both physiological effectiveness and sustainable engagement.

Bibliography

[1] Ajzen, I. (1991). *The theory of planned behavior*. Organizational Behavior and Human Decision Processes, 50(2), 179–211.

[2] Alam, R., Zhao, H., Goodwin, A., Kavehei, O., & McEwan, A. (2020). *Differences in power spectral densities and phase quantities due to processing of EEG signals*. Sensors, 20(21), 6285.

[3] Al-Fahoum, A. S., & Al-Fraihat, A. A. (2014). *Methods of EEG signal feature extraction using linear analysis in frequency and time–frequency domains*. International Scholarly Research Notices, 2014, 1–7.

[4] Allen, J. J. B., Coan, J. A., & Nazarian, M. (2004). *Issues and assumptions on the road from raw signals to metrics of frontal EEG asymmetry in emotion*. Biological Psychology, 67(1–2), 183–218.

[5] Astorino, T. A., & Thum, J. S. (2018). *Interval training elicits higher enjoyment versus moderate exercise in persons with spinal cord injury*. Journal of Spinal Cord Medicine, 41(1), 77–84.

[6] Astorino, T. A., Clark, A., De La Rosa, A., & De Revere, J. (2019). *Enjoyment and affective responses to two regimes of high-intensity interval training in inactive women with obesity*. European Journal of Sport Science, 19(10), 1377–1385.

[7] Ballor, D. L., & Volovsek, A. J. (1992). *Effect of exercise-to-rest ratio on plasma lactate concentration at work rates above and below maximum oxygen uptake*. European Journal of Applied Physiology, 65, 365–369.

[8] Bandura, A. (1998). *Health promotion from the perspective of social cognitive theory*. Psychology & Health, 13, 623–649.

[9] Beauchamp, M. K., Nonoyama, M., Goldstein, R. S., Hill, K., Dolmage, T. E., Mathur, S., & Brooks, D. (2010). *Interval versus continuous training in individuals with chronic obstructive pulmonary disease: A systematic review*. Thorax, 65, 157–164.

[10] Biddle, S. J. H., & Batterham, A. M. (2015). *High–intensity interval exercise training for public health: A big HIT or shall we HIT it on the head?*. International Journal of Behavioral Nutrition and Physical Activity, 12, Article 95.

[11] Billat, V. L., Renoux, J. C., Pinoteau, J., Petit, B., & Koralsztein, J. P. (1994). *Times to exhaustion at 100% of velocity at $VO_{2\,\max}$ and modeling of the time-limit/velocity relationship in elite long-distance runners*. European Journal of Applied Physiology, 69, 271–283.

[12] Billat, V. L. (2001). *Interval training for performance: A scientific and empirical practice. Part I. Aerobic interval training*. Sports Medicine, 31(1), 3–31.

[13] Bitsika, V., Sharpley, C. F., Evans, I. D., & Vessey, K. A. (2024). *Neurological validation of ASD diagnostic criteria using frontal alpha and theta asymmetry*. Journal of Clinical Medicine, 13(16), 4876.

[14] Bixby, W. R., Spalding, T. W., & Hatfield, B. D. (2001). *Temporal dynamics and dimensional specificity of the affective response to exercise of varying intensity: Differing pathways to a common outcome*. Journal of Sport & Exercise Psychology, 23, 171–190.

[15] Borg, G. A. (1982). *Psychophysical bases of perceived exertion*. Medicine & Science in Sports & Exercise, 14, 377–381.

[16] Borg, G. A. V. (1998). *Borg's perceived exertion and pain scales*. Human Kinetics.

[17] Borod, J. C., Haywood, C. S., & Koff, E. (1997). *Neuropsychological aspects of facial asymmetry during emotional expression: A review of the normal adult literature*. Neuropsychology Review, 7, 41–60.

[18] Boutcher, S. H., & Landers, D. M. (1988). *The effects of vigorous exercise on anxiety, heart rate, and alpha activity of runners and nonrunners.*. *Psychophysiology*, 25(6), 696–702.

[19] Bryan, A., Hutchison, K. E., Seals, D. R., & Allen, D. L. (2007). *A transdisciplinary model integrating genetic, physiological, and psychological correlates of voluntary exercise*. Health Psychology, 26, 30–39.

[20] Cacioppo, J. T., Tassinary, L. G., & Fridlund, A. J. (1990). *The skeletomotor system*. In J. T. Cacioppo & L. G. Tassinary (Eds.), *Principles of psychophysiology: Physical, social, and inferential elements* (pp. 325–384). Cambridge University Press.

[21] Cavanagh, J. F., & Frank, M. J. (2014). *Frontal theta as a mechanism for cognitive control*. Trends in Cognitive Sciences, 18(8), 414–421.

[22] Christmass, M. A., Dawson, B., & Arthur, P. G. (1999). *Effect of work and recovery duration on skeletal muscle oxygenation and fuel use during sustained intermittent exercise*. European Journal of Applied Physiology, 80, 436–447.

[23] Christmass, M. A., Dawson, B., Passeretto, P., & Arthur, P. G. (1999). *A comparison of skeletal muscle oxygenation and fuel use in sustained continuous and intermittent exercise*. European Journal of Applied Physiology, 80, 423–435.

[24] Ciria, L. F., Luque-Casado, A., Sanabria, D., Holgado, D., Ivanov, P. C., & Perakakis, P. (2019). *Oscillatory brain activity during acute exercise: Tonic and transient neural response to an oddball task.*. *Psychophysiology*, 56(5), e13326.

[25] Coan, J. A., Allen, J. J. B., & Harmon-Jones, E. (2001). *Voluntary facial expression and hemispheric asymmetry over the frontal cortex*. Psychophysiology, 38(6), 912–925.

[26] da Silva, D. F., Ferraro, Z. M., Adamo, K. B., & Machado, F. A. (2019). *Endurance running training individually guided by heart rate variability in untrained women*. Journal of Strength and Conditioning Research, 33(3), 736–746.

[27] Davidson, R. J. (1988). *EEG measures of cerebral asymmetry: Conceptual and methodological issues*. International Journal of Neuroscience, 39(1–2), 71–89.

[28] Davidson, R. J., Marshall, J. R., Tomarken, A. J., & Henriques, J. B. (2000). *While a phobic waits: Regional brain electrical and autonomic activity in social phobics during anticipation of public speaking*. Biological Psychiatry, 47(2), 85–95.

[29] Decker, E. S., & Ekkekakis, P. (2017). *More efficient, perhaps, but at what price? Pleasure and enjoyment responses to high-intensity interval exercise in low-active women with obesity*. Psychology of Sport and Exercise, 28, 1–10.

[30] Dussault, C., Jouanin, J. C., Philippe, M., & Guezennec, C. Y. (2005). *EEG and ECG changes during simulator operation reflect mental workload and vigilance*. Aviation, Space, and Environmental Medicine, 76(4), 344–351.

[31] Ekkekakis, P. (2003). *Pleasure and displeasure from the body: Perspectives from exercise*. Cognition and Emotion, 17(2), 213–239.

[32] Ekkekakis, P., Parfitt, G., & Petruzzello, S. J. (2011). *The pleasure and displeasure people feel when they exercise at different intensities: Decennial update and progress towards a tripartite rationale for exercise intensity prescription*. Sports Medicine, 41(8), 641–671.

[33] Ekkekakis, P., Hargreaves, E. A., & Parfitt, G. (2013). *Invited Guest Editorial: Envisioning the next fifty years of research on the exercise–affect relationship*. Psychology of Sport and Exercise, 14(5), 751–758.

[34] Ekkekakis, P. (2017). *People have feelings! Exercise psychology in paradigmatic transition*. Current Opinion in Psychology, 16, 84–88.

[35] Ekkekakis, P., Swinton, P., & Tiller, N. B. (2023). *Extraordinary claims in the literature on high-intensity interval training (HIIT): I. Bonafide scientific revolution or a looming crisis of replication and credibility?*. Sports Medicine.

[36] Farias-Junior, L. F., Macedo, G. A. D., Browne, R. A. V., Freire, Y. A., Oliveira-Dantas, F. F., Schwade, D., Mortatti, A. L., Santos, T. M., & Costa, E. C. (2019). *Physiological and psychological responses during low-volume high-intensity interval training sessions with different work–recovery durations*. Journal of Sports Science and Medicine, 18, 181–190.

[37] FieldTrip Toolbox. *Independent Component Analysis (ICA) to remove EOG artifacts*. Retrieved August 15, 2025, from `https://www.fieldtriptoolbox.org/example/preproc/ica_eog/`

[38] Franch, J., Madsen, K., Djurhuus, M. S., & Pedersen, P. K. (1998). *Improved running economy following intensified training correlates with reduced ventilatory demands*. Medicine & Science in Sports & Exercise, 30, 1250–1256.

[39] Frazão, D. T., de Farias Junior, L. F., Dantas, T. C. B., Krinski, K., Elsangedy, H. M., Prestes, J., Hardcastle, S. J., & Costa, E. C. (2016). *Feeling of pleasure to high-intensity interval exercise is dependent on the number of work bouts and physical activity status*. PLoS ONE, 11(4), e0152752.

[40] Friedman, B. H., & Thayer, J. F. (1991). *Facial muscle activity and EEG recordings—redundancy analysis*. Electroencephalography and Clinical Neurophysiology, 79, 358–360.

[41] Gasser, T., Sroka, L., & Mocks, J. (1985). *The transfer of EOG activity into the EEG for eyes open and closed*. Electroencephalography and Clinical Neurophysiology, 61(2), 181–193.

[42] Gibala, M. J. (2007). *High-intensity interval training: A time-efficient strategy for health promotion?*. Current Sports Medicine Reports, 6(4), 211–213.

[43] Gibala, M. J., & McGee, S. L. (2008). *Metabolic adaptations to short-term high-intensity interval training: A little pain for a lot of gain?*. Exercise and Sport Sciences Reviews, 36(2), 58–63.

[44] Gibala, M. J., Gillen, J. B., & Percival, M. E. (2014). *Physiological and health-related adaptations to low-volume interval training: Influences of nutrition and sex*. Sports Medicine, 44, S127–S137.

[45] Gramkow, M. H., Hasselbalch, S. G., Waldemar, G., & Frederiksen, K. S. (2020). *Resting-state EEG in exercise intervention studies: A systematic review of effects and methods*. Frontiers in Neuroscience, 14, 155.

[46] Gratton, G. (1998). *Dealing with artifacts: The EOG contamination of the event-related brain potential*. Behavior Research Methods, Instruments, & Computers, 30(1), 44–53.

[47] Gropper, H., John, J. M., Sudeck, G., & Thiel, A. (2023). *"I just had the feeling that the interval training is more beneficial": Young adults' subjective experiences of physical fitness and the role of training modes*. Frontiers in Sports and Active Living, 5, 111594.

[48] Hagemann, D., Naumann, E., & Thayer, J. F. (2001). *The quest for the EEG reference revisited: A glance from brain asymmetry research*. Psychophysiology, 38(5), 847–857.

[49] Hall, J. F. (1976). *Classical conditioning and instrumental learning: A contemporary approach*. Philadelphia, PA: Lippincott.

[50] Hardcastle, S. J., Ray, H., Beale, L., & Hagger, M. S. (2014). *Why sprint interval training is inappropriate for a largely sedentary population*. Frontiers in Psychology, 5, Article 1505.

[51] Hardy, C. J., & Rejeski, W. J. (1989). *Not what, but how one feels: The measurement of affect during exercise*. Journal of Sport and Exercise Psychology, 11(3), 304–317.

[52] Heller, W. (1990). *The neuropsychology of emotion: Developmental patterns and implications for psychopathology*. In N. L. Stein, B. Leventhal, & T. Trabasso (Eds.), *Psychological and biological approaches to emotion* (pp. 167–211). Lawrence Erlbaum Associates.

[53] Heller, W. (1993). *Neuropsychological mechanisms of individual differences in emotion, personality, and arousal*. Neuropsychology, 7(4), 476–489.

[54] Iacono, W. G., & Lykken, D. T. (1981). *Two-year retest stability of eye tracking performance and a comparison of electro-oculographic and infrared recording techniques*. Psychophysiology, 18(1), 49–55.

[55] Jung, M. E., Bourne, J. E., & Little, J. P. (2014). *Where does HIT fit? An examination of the affective response to high-intensity intervals in comparison to continuous moderate- and continuous vigorous-intensity exercise in the exercise intensity–affect continuum*. PLoS ONE, 9(12), e114541.

[56] Kendzierski, D., & DeCarlo, K. J. (1991). *Physical activity enjoyment scale: Two validation studies*. Journal of Sport and Exercise Psychology, 13(1), 50–64.

[57] Kilpatrick, M. W., Jung, M. E., & Little, J. P. (2014). *High-intensity interval training: A review of physiological and psychological responses*. ACSM's Health & Fitness Journal, 18(5), 11–16.

[58] Kilpatrick, M. W., Martinez, N., Little, J. P., Jung, M. E., Jones, A. M., Price, N. W., & Lende, D. H. (2015). *Impact of high-intensity interval duration on perceived exertion*. Medicine & Science in Sports & Exercise, 47(5), 1038–1045.

[59] Kilpatrick, M. W., Greeley, S. J., & Collins, L. H. (2015). *The impact of continuous and interval cycle exercise on affect and enjoyment*. Research Quarterly for Exercise and Sport, 86(3), 244–251.

[60] Knechtle, B., & Nikolaidis, P. T. (2018). *Sex- and age-related differences in half-marathon performance and competitiveness in the world's largest half-marathon: The GöteborgsVarvet*. Research in Sports Medicine, 26(1), 75–85.

[61] Kubitz, K. A., & Pothakos, K. (1997). *Does aerobic exercise decrease brain activation?*. Research Quarterly for Exercise and Sport, 67(3), 291–301.

[62] Kuipers, H., Verstappen, F. T., Keizer, H. A., Geurten, P., & van Kranenburg, G. (1985). *Variability of aerobic performance in the laboratory and its physiologic correlates*. International Journal of Sports Medicine, 6(4), 197–201.

[63] Machado, F. A., Kravchychyn, A. C. P., Peserico, C. S., da Silva, D. F., & Mezzaroba, P. V. (2013). *Incremental test design, peak aerobic running speed, and endurance performance in runners*. Journal of Science and Medicine in Sport, 16(6), 577–582.

[64] Manstead, A. S. R., & Parker, D. (1995). *Evaluating and extending the Theory of Planned Behaviour*. European Review of Social Psychology, 6, 69–95.

[65] Marcora, S. M. (2009). *Perception of effort during exercise is independent of afferent feedback from skeletal muscles, heart, and lungs*. Journal of Applied Physiology, 106(6), 2060–2062.

[66] Martinez, N., Kilpatrick, M. W., Salomon, K., Jung, M. E., & Little, J. P. (2015). *Affective and enjoyment responses to high-intensity interval training in overweight-to-obese and insufficiently active adults*. Journal of Sport and Exercise Psychology, 37, 138–149.

[67] McNair, D., Lorr, M., & Droppleman, L. (1971). *POMS manual for the Profile of Mood States*. San Diego, CA: Educational and Industrial Testing Service.

[68] Midgley, A. W., McNaughton, L. R., & Carroll, S. (2007). *Effect of the* VO_2 *time-averaging interval on the reproducibility of* $VO_{2\,\max}$ *in healthy athletic subjects*. Clinical Physiology and Functional Imaging, 27(2), 122–125.

[69] Mierau, A., Schneider, S., Abel, T., Askew, C., Werner, S., & Strüder, H. K. (2009). *Improved sensorimotor adaptation after exhaustive exercise is accompanied by altered brain activity*. Physiology & Behavior, 96(1), 115–121.

[70] Morgan, W. P. (1980). *The trait psychology controversy*. Research Quarterly for Exercise and Sport, 51(1), 50–76.

[71] Niven, A., Laird, Y., Saunders, D. H., & Phillips, S. M. (2021). *A systematic review and meta-analysis of affective responses to acute high-intensity interval exercise compared with continuous moderate- and high-intensity exercise*. Health Psychology Review, 15(4), 540–574.

[72] Oliveira, B. R. R., Slama, F. A., Deslandes, A. C., Furtado, E. S., & Santos, T. M. (2013). *Continuous and high-intensity interval training: Which promotes higher pleasure?*. PLoS ONE, 8(11), e79965.

[73] Oliveira, B. R. R., Santos, T. M., Kilpatrick, M., Pires, F. O., & Deslandes, A. C. (2018). *Affective and enjoyment responses in high-intensity interval training and continuous training: A systematic review and meta-analysis*. PLoS ONE, 13(6), e0197124.

[74] Olney, N., Wertz, T., Laporta, Z., Mora, A., Serbas, J., & Astorino, T. A. (2018). *Comparison of acute physiological and psychological responses between moderate-intensity continuous exercise and three regimes of high-intensity interval training*. Journal of Strength and Conditioning Research, 32(8), 2130–2138.

[75] Pageaux, B., Marcora, S. M., & Lepers, R. (2013). *Prolonged mental exertion does not alter neuromuscular function of the knee extensors*. Medicine & Science in Sports & Exercise, 45(12), 2254–2264.

[76] Pan, N., Fang, Z., Wang, J., & Cao, P. (2024). *Frontal theta asymmetry may be a new target for reducing the severity of depression and improving cognitive function in depressed patients*. Journal of Affective Disorders.

[77] Paterson, D. H., Shephard, R. J., Cunningham, D., Jones, N. L., & Andrew, G. (1979). *Effects of physical training on cardiovascular function following myocardial infarction*. Journal of Applied Physiology: Respiratory, Environmental and Exercise Physiology, 47, 482–489.

[78] Petruzzello, S. J., & Landers, D. M. (1994). *State anxiety reduction and exercise: Does hemispheric activation reflect such changes?* Medicine & Science in Sports & Exercise, 26(8), 1028–1035.

[79] Petruzzello, S. J., Hall, E. E., & Ekkekakis, P. (2001). *Regional brain activation as a biological marker of affective responsivity to acute exercise: Influence of fitness*. *Psychophysiology*, 38(1), 99–106.

[80] Petruzzello, S. J., Hall, E. E., & Ekkekakis, P. (2007). *Brain activation, affect, and aerobic exercise: An examination of both state-independent and state-dependent relationships*. Journal of Sport and Exercise Psychology, 29(5), 527–533.

[81] Picton, T. W., Bentin, S., Berg, P., Donchin, E., Hillyard, S. A., & Johnson, R. (2000). *Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria*. Psychophysiology, 37(2), 127–152.

[82] Prapavessis, H. (2000). *The Profile of Mood States and sport performance: A review*. Journal of Applied Sport Psychology, 12(1), 34–48.

[83] Price, M. J., & Halabi, K. (2005). *The effects of work:rest duration on intermittent exercise and subsequent performance*. Journal of Sports Sciences, 23, 835–842.

[84] Price, M., & Moss, P. (2007). *The effects of work:rest duration on physiological and perceptual responses during intermittent exercise and performance*. Journal of Sports Sciences, 25, 1613–1621.

[85] Racil, G., Ben Ounis, O., Hammouda, O., Kallel, A., Zouhal, H., Chamari, K., & Amri, M. (2013). *Effects of high vs. moderate exercise intensity during interval training on lipids and adiponectin levels in obese young females*. European Journal of Applied Physiology, 113, 2531–2540.

[86] Radüntz, T., Scouten, J., Hochmuth, O., & Meffert, B. (2017). *Automated EEG artifact elimination by applying machine learning algorithms to ICA-based features*. Journal of Neural Engineering, 14(3), 036003.

[87] Rhodes, R. E., & Kates, A. (2015). *Can the affective response to exercise predict future motives and physical activity behavior? A systematic review of published evidence*. Annals of Behavioral Medicine, 49, 715–731.

[88] Robertson, R. J., & Noble, B. J. (1997). *Perception of physical exertion: Methods, mediators, and applications*. Exercise and Sport Science Reviews, 25, 407–452.

[89] Roloff, Z. A., Dicks, N. D., Krynski, L. M., Hartman, M. E., Ekkekakis, P., & Pettitt, R. W. (2020). *Ratings of affective valence closely track changes in oxygen uptake: Application to high-intensity interval exercise*. Performance Enhancement & Health, 7(3–4), Article 100158.

[90] Schneider, S., Askew, C. D., Diehl, J., Mierau, A., Kleinert, J., Abel, T., Carnahan, H., & Strüder, H. K. (2009). *EEG activity and mood in health-oriented runners after different exercise intensities*. Physiology & Behavior, 96(4–5), 709–716.

[91] Silveira, R., Prado, R. C. R., Brietzke, C., Coelho-Júnior, H. J., Santos, T. M., Pires, F. O., & Asano, R. Y. (2019). *Prefrontal cortex asymmetry and psychological responses to exercise: A systematic review*. Physiology & Behavior, 212, 112580.

[92] Smodlaka, V. N. (1972). *Use of the interval work capacity test in the evaluation of severely disabled patients*. Journal of Chronic Diseases, 25, 345–352.

[93] Stork, M. J., Banfield, L. E., Gibala, M. J., & Martin Ginis, K. A. (2017). *A scoping review of the psychological responses to interval exercise: Is interval exercise a viable alternative to traditional exercise?*. Health Psychology Review, 11(4), 324–344.

[94] Stork, M. J., Gibala, M. J., & Martin Ginis, K. A. (2018). *Psychological and behavioral responses to interval and continuous exercise*. Medicine & Science in Sports & Exercise, 50(10), 2110–2121.

[95] Tan, E., Troller-Renfree, S. V., Morales, S., Buzzell, G. A., McSweeney, M., Antúnez, M., & Fox, N. A. (2023). *Theta activity and cognitive functioning: Integrating evidence from resting-state and task-related developmental electroencephalography (EEG) research*. OSF Preprints.

[96] Thum, J. S., Parsons, G., Whittle, T., & Astorino, T. A. (2017). *High-intensity interval training elicits higher enjoyment than moderate-intensity continuous exercise*. PLoS ONE, 12(1), e0166299.

[97] Tomarken, A. J., & Davidson, R. J. (1994). *Frontal brain activation in repressors and nonrepressors*. Journal of Abnormal Psychology, 103(2), 339–349.

[98] Viana, R. B., Lira, C. A. B., Naves, J. P. A., Coswig, V. S., Del Vecchio, F. B., Ramírez-Campillo, R., Vieira, C. A., & Gentil, P. (2018). *Can we draw general conclusions from interval training studies?*. Sports Medicine, 48(9), 2001–2017.

[99] Weston, K. S., Wisløff, U., & Coombes, J. S. (2014). *High-intensity interval training in patients with lifestyle-induced cardiometabolic disease: A systematic review and meta-analysis*. British Journal of Sports Medicine, 48(16), 1227–1234.

[100] Williams, D. M. (2008). *Exercise, affect, and adherence: An integrated model and a case for self-paced exercise*. Journal of Sport and Exercise Psychology, 30, 471–496.

[101] Woo, M., Kim, S., Kim, J., Petruzzello, S. J., & Hatfield, B. D. (2009). *Examining the exercise–affect dose–response relationship: Does duration influence frontal EEG asymmetry?*. International Journal of Psychophysiology, 72(2), 166–172.

[102] Woo, M., Kim, S., Kim, J., Petruzzello, S. J., & Hatfield, B. D. (2010). *The influence of exercise intensity on frontal electroencephalographic asymmetry and self-reported affect.*. *Research Quarterly for Exercise and Sport*, 81(3), 349–359.

[103] Yeung, R. R. (1996). *The acute effects of exercise on mood state*. Journal of Psychosomatic Research, 40(2), 123–141.

[104] Youngstedt, S. D., Dishman, R. K., Cureton, K. J., & Peacock, L. J. (1993). *Does body temperature mediate anxiolytic effects of acute exercise?* Journal of Applied Physiology, 74(2), 825–831.

[105] Zhang, H., Zhou, Q. Q., Chen, H., et al. (2023). *The applied principles of EEG analysis methods in neuroscience and clinical neurology*. Military Medical Research.

Appendix A

Supplementary Code

A.1 Data import snippet

```
from visit_psychological import df_psychological as df_psych
from visit_physiological import df_physiological as df_phys
```

A.2 Band-power computation snippet

```
band_power = 10 * np.log10(psd.get_data().mean(axis=1))
```

Appendix B

Additional Data and Figures

B.1 Detailed EEG Analysis and Behavioral Correlation Pipeline

B.1.1 Libraries and Dependencies

The analysis utilized MNE, Pandas, NumPy, SciPy, Statsmodels, Seaborn, and Matplotlib for EEG processing, data manipulation, statistical analysis, and visualization.

B.1.2 Configuration and Setup

Data paths, participant lists, experimental conditions (PS, PH),
states (REST, TETRIS), timepoints (PRE, POST), and EEG frequency bands
(Theta 4–8 Hz, Alpha 8–13 Hz) were defined. Artifact channels were excluded.