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**Study of Recording and Analysis of Multi-Source
Data for the Estimation of Emotion Indicators**

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ΠΟΛΥΤΕΧΝΕΙΟ ΚΡΗΤΗΣ
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Πολυτεχνείο Κρήτης

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Abstract

Human emotions profoundly influence our cognitive performance, physiological body responses, and overall well-being, yet objectively measuring these emotional states in real-world environments remains a significant challenge. This diploma focuses on developing a multi-device system capable of simultaneously recording and analyzing physiological body signals from multiple sources to detect emotional responses to different stimuli within an immersive projection environment. This experiment was conducted in the context of a collaboration between the Display Lab (School of Electrical and Computer Engineering) and the Transformable Intelligent Environments Lab (TIE Lab, School of Architecture) at the Technical University of Crete.

During the experiment, multimodal physiological body data (EEG and ECG) were collected from 33 participants, as they watched two different videos within an immersive audiovisual setup. The analysis focused primarily on the first video, which contained six segments that alternated between stress-inducing and calming content, while the second featured four continuously peaceful blue space scenes. EEG data were recorded using the Unicorn Hybrid Black system and ECG measurements were captured through two wearable devices: the Movesense chest strap and the Traqbeat wristband.

Signal processing tools that were used included MATLAB for EEG bandpass filtering and preprocessing, Python with dyconnmap for dynamic brain connectivity analysis, Neural Gas clustering algorithms for signal complexity quantification, and SciPy for ECG R-peak detection and heart rate variability analysis. Key methodological innovations included chronnectomics analysis using weighted Phase Lag Index (wPLI) for brain state transitions, adaptive R-peak detection with Butterworth filtering, and multimodal feature fusion. The results demonstrate reliable inference of emotional states through brain state flexibility, cognitive patterns, and cardiovascular measures, with stress conditions showing significantly reduced neural adaptability and increased cardiac irregularity compared to calm states. The integrated approach enables objective classification of emotional states, establishing biomarkers for stress versus relaxation in real-time monitoring systems.

This research demonstrates how effectively multimodal biosignal analysis can distinguish emotional responses to different audiovisual stimuli. These findings open up new horizons, both in clinical settings and in applications of deeper psychological assessment.

Περίληψη

Τα ανθρώπινα συναισθήματα επηρεάζουν βαθιά τη γνωστική μας απόδοση, τις φυσιολογικές αντιδράσεις του σώματος και τη συνολική μας ευεξία, ωστόσο η μέτρηση αυτών των συναισθηματικών καταστάσεων σε περιβάλλοντα πραγματικού κόσμου παραμένει μια σημαντική πρόκληση. Η παρούσα διπλωματική εργασία επικεντρώνεται στην ανάπτυξη ενός συστήματος πολλαπλών συσκευών που είναι ικανό να καταγράφει και να αναλύει ταυτόχρονα φυσιολογικά σήματα σώματος από πολλαπλές πηγές για την ανίχνευση συναισθηματικών αντιδράσεων σε διάφορα ερεθίσματα, μέσα σε ένα περιβάλλον εμπιστευτικής προβολής. Το πείραμα αυτό, διεξήχθη στο πλαίσιο συνεργασίας του Display Lab (Σχολή Ηλεκτρολόγων Μηχανικών και Μηχανικών Υπολογιστών) και του Transformable Intelligent Environments Lab (TIE Lab, Σχολή Αρχιτεκτόνων) του Πολυτεχνείου Κρήτης.

Κατά τη διάρκεια του πειράματος, συλλέχθηκαν πολυτροπικά φυσιολογικά σήματα σώματος (EEG και ECG) από 33 συμμετέχοντες, κατά τη διάρκεια παρακολούθησης δύο διαφορετικών βίντεο σε ένα διαδραστικό οπτικοακουστικό περιβάλλον. Η ανάλυση επικεντρώθηκε κυρίως στο πρώτο βίντεο, το οποίο περιείχε έξι ερεθίσματα που εναλλάσσονταν μεταξύ στρεσογόνου και ήρεμου περιεχομένου, ενώ το δεύτερο παρουσίαζε τέσσερις σκηνές, με διαρκή αίσθηση ηρεμίας. Τα δεδομένα EEG καταγράφηκαν με το σύστημα Unicorn Hybrid Black και τα δεδομένα ECG με δύο φορητές συσκευές: τη ζώνη στήθους Movesense και το περικάρπιο Traqbeat.

Χρησιμοποιήθηκαν διάφορα εργαλεία επεξεργασίας σήματος, όπως το MATLAB για το ζωνοπερατό φιλτράρισμα και την προεπεξεργασία του ΗΕΓ, η Python με το `dyconnmap` για τη δυναμική ανάλυση της συνδεσιμότητας του εγκεφάλου, οι αλγόριθμοι ομαδοποίησης Neural Gas για την ποσοτικοποίηση της πολυπλοκότητας του σήματος και το SciPy για την ανίχνευση των κορυφών R του ΗΚΓ και την ανάλυση της μεταβλητότητας του καρδιακού ρυθμού. Η βασική μεθοδολογία, περιλάμβανε την ανάλυση *chronnectomics* με χρήση της μεθόδου *wPLI* για τις μεταβάσεις της κατάστασης του εγκεφάλου, την προσαρμοστική ανίχνευση R-peak με φιλτράρισμα Butterworth και την πολυτροπική σύντηξη χαρακτηριστικών. Τα αποτελέσματα αποδεικνύουν την εξαγωγή συμπερασμάτων για τις συναισθηματικές καταστάσεις μέσω της ευελιξίας των εγκεφαλικών καταστάσεων, με τις συνθήκες άγχους να παρουσιάζουν σημαντικά μειωμένη νευρική προσαρμοστικότητα και αυξημένη καρδιακή λειτουργία σε σύγκριση με τις ήρεμες καταστάσεις. Η ολοκληρωμένη αυτή προσέγγιση επιτρέπει την ταξινόμηση συναισθηματικών καταστάσεων, καθιερώνοντας βιοδείκτες για το άγχος έναντι της χαλάρωσης σε συστήματα παρακολούθησης πραγματικού χρόνου.

Η έρευνα αυτή αποδεικνύει πόσο αποτελεσματικά μπορεί η ανάλυση πολυτροπικών βιοσημάτων να διακρίνει συναισθηματικές αντιδράσεις σε διαφορετικά οπτικοακουστικά ερεθίσματα. Τα ευρήματα αυτά διανοίγουν νέους ορίζοντες, τόσο σε κλινικά περιβάλλοντα, όσο και σε εφαρμογές βαθύτερης ψυχολογικής αξιολόγησης.

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Contents

Abstract	2
Περίληψη	3
Acknowledgements	5
List of Abbreviations	14
1 Introduction	15
1.1 Motivation and Innovation	15
1.2 Research Objectives	17
1.3 Thesis Organization	18
2 Literature Review	19
2.1 Introduction	19
2.2 Physiological Correlates of Emotional States	19
2.2.1 Central Nervous System Responses: EEG	19
2.2.2 Autonomic Nervous System Responses: ECG and HRV	20
2.3 Analysis of Blue Spaces, Immersive Projection, and Virtual Reality	20
2.3.1 Virtual Reality versus Immersive Projection in Emotion Research	21
2.4 Multimodal Emotion Recognition	23
2.4.1 Advantages of Multimodal Approaches	23
3 Experimental Methodology	24
3.1 Participants	24
3.2 Experimental Design	25
3.2.1 Research Hypotheses Framework	25
3.2.2 Variable Classification	26
3.3 Experimental Environment	26

3.3.1	Location: Sabbionara Gate Historical Venue	26
3.4	Stimulus Materials	28
3.4.1	Video 1: Mixed Emotional Content Sequence	28
3.4.2	Video 2: Blue Space Immersion Protocol	31
3.5	Equipment	31
3.5.1	EEG Recording System: Unicorn Hybrid Black	31
3.5.2	ECG Recording Systems	32
3.5.3	Data Acquisition & Synchronization	34
3.6	Experimental Procedure	35
3.6.1	Pre-Experiment Phase (15 minutes)	35
3.6.2	Experimental Phase (~20 minutes)	39
3.6.3	Post-Experiment Phase (5 minutes)	40
4	Signal Processing and Analysis Methods	41
4.1	Dataset Acquisition	41
4.1.1	Participant Selection and Exclusion Criteria	41
4.1.2	Experimental Protocol	42
4.1.3	Hardware & Recording Settings	43
4.1.4	Raw Data Organization	44
4.2	ECG Preprocessing	45
4.2.1	ECG Signal Processing and Analysis	47
4.2.2	Data Acquisition	47
4.2.3	Signal Preprocessing Pipeline	47
4.2.4	R-Peak Detection	48
4.2.5	R-R Interval Extraction and Quality Control	49
4.2.6	Heart Rate Variability Metrics	49
4.2.7	ECG Statistical Analysis	50
4.3	EEG Signal Processing Pipeline	52
4.3.1	Step 1: Data Preparation and Cleaning	52
4.3.2	Step 2: Initial Signal Preprocessing Pipeline (Matlab)	53

4.3.3	EEG: Initial Feature Extraction Methods	54
4.3.4	Step 3: Connectivity Analysis	56
4.3.5	EEG Statistical Analysis	59
5	Results	61
5.1	Questionnaire Results	61
5.1.1	Selection Criteria	61
5.1.2	Final Sample Demographics	61
5.1.3	Questionnaire Data Summary	62
5.2	ECG Analysis Results	65
5.2.1	ECG Data Processing and Quality Control	65
5.2.2	Heart Rate Variability Analysis	66
5.2.3	Statistical Analysis Results: ECG	67
5.2.4	Pairwise Comparisons	68
5.2.5	Key Findings	69
5.3	EEG Analysis Results	70
5.3.1	Connectivity Method Comparison and Selection	70
5.3.2	Neural Gas Analysis	74
5.3.3	Statistical Analysis Results: ECG	75
6	Discussion	79
6.1	Overview	79
6.2	Principal Findings and Theoretical Implications	79
6.2.1	Validation of Dimensional Emotion Theory Through Physiological Markers	79
6.3	Methodological Contributions and Innovations	80
6.3.1	Advancing Chronnectomics for Emotion Recognition	80
6.3.2	Validity Through Immersive Projection	80
6.4	Issues: Temperature and Technology Limitations	81
6.4.1	Temperature Control and Environmental Standardization	81
6.4.2	Current System Limitations and Complexity:	82

7	Future Work and Considerations	83
7.1	Advanced Data Integration and Machine Learning Applications	83
7.1.1	Machine Learning Integration for Emotion Recognition	83
7.1.2	Future Integrated Systems	83
7.2	Therapeutic and Climate Controlled Environments	84
7.2.1	Decompression Rooms	85
7.2.2	Methodological Enhancements	85
7.2.3	Broader Implications for Physiological Research	86
7.3	Conclusion	87

List of Figures

1.1	Experimental setup at the Sabbionara Gate - Blue Space Stimulus.	16
1.2	Thesis structure: From theoretical foundations through experimental innovation to practical insights	18
2.1	Comparison between immersive projection and virtual reality as used in the experimental design.	21
2.2	Immersive projection environment used for audiovisual stimulus presentation.	23
3.1	The Sabbionara Gate experimental location located in Chania, Crete. [30]	26
3.2	Interior view of the Sabbionara Gate. [30]	27
3.3	Snapshots from the six video stimuli used in the experiment.	29
3.4	Snapshots of real participants during the experiment, watching the six video stimuli inside the immersive projection space.	30
3.5	EEG Recording System Setup and Application	31
3.6	Movesense ECG chest strap positioning between 3rd and 4th ribs for optimal R-wave detection[29]	32
3.7	Traqbeat wrist monitor placement for backup monitoring and movement detection [38]	33
3.8	Main computing platforms and software used for data acquisition and synchronization.	34
3.9	EEG Preparation Process	36
3.10	ECG Preparation Process	36
3.11	Self-Assessment Manikin (SAM) pictorial scales used for emotional assessment.	38
3.12	Experimental setup along with the participant seated at the center with EEG and ECG devices.	39
4.1	Data acquisition setup: EEG via Unicorn headset into a Windows laptop, wrist and chest-worn ECG devices into a Raspberry Pi.	43
4.2	Comparison of raw ECG signals from and Movesense (top) and Traqbeat (bottom) devices for the same participant.	45

4.3	Complete ECG signal processing for Video 1: Beach1 (pink), Shark Attack (orange), Rollercoaster (green), Nature (blue), Night Walk (purple), and Beach2 (light pink). Red dots mark detected R-peaks across the entire 414s recording.	46
4.4	R-peak detection verification on filtered ECG, detected R-peaks (red dots).	48
4.5	Raw EEG data from Subject 31 showing all 8 channels with notable artifacts.	52
4.6	Filtered EEG data from the same Subject 31 after application of the complete preprocessing pipeline.	53
4.7	Averaged PSD by Channel, Across All Subjects	54
4.8	Averaged MF Values, Per Stimulus	55
4.9	P-Values, Wilcoxon Signed Rank Test	55
5.1	Lifestyle Factor Answers.	62
5.2	Stress: Current and Monthly.	63
5.3	Prevalence of self-reported phobias among male and female participants.	64
5.4	SAM Results.	65
5.5	HRV metrics across stimulus conditions shown as bar plots with standard error bars. Entropy showed significant group differences (ANOVA $p = 0.037$), while other metrics showed no significant effects.	66
5.6	Distribution of HRV metrics across stimulus conditions shown as violin plots. Entropy again displays the clearest difference between stimuli.	67
5.7	Individual HRV metrics showing significant pairwise comparisons (uncorrected p -values). (a) Entropy demonstrated significant differences between Shark Attack and both Nature conditions. (b) Skewness showed one significant comparison between Rollercoaster and Nature. Significance bars indicate uncorrected p -values: ** $p < 0.01$, * $p < 0.05$	69
5.8	HRV metrics showing no significant pairwise comparisons. Both Power and SDNN demonstrated similar distributions across stimulus conditions with no statistically significant differences between stress and calm conditions.	69
5.9	Comprehensive comparison of chronnectomics metrics across three connectivity methods. Top row shows stimulus-specific comparisons for (a) Flexibility Index, (b) Mean Dwell Time, and (c) Occupancy Entropy. Bottom row displays overall distributions across all stimuli and subjects for each connectivity method.	71

5.10 Chronnectomics Metrics	72
5.11 Chronnectomics Metrics - Barplots	72
5.12 Neural Gas final quantization error across stimulus conditions. Higher final errors in stress conditions (Shark Attack, Rollercoaster, Night Walk) versus calming conditions (Nature, Beach).	74
5.13 Statistical analysis of brain state flexibility across stimulus conditions. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	76
5.14 Statistical analysis of brain state persistence across stimulus conditions. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	77
5.15 Statistical analysis of occupancy entropy across stimulus conditions. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	78
6.1 Temperature progression throughout the experiment showing increase from 33.3°C to 36.4°C over the 25-minute session duration. The vertical dashed line indicates the transition from Video 1 to Video 2 stimuli presentation. .	81
7.1 Virtual Decompression Room. [24]	85

List of Tables

3.1	Research Hypotheses Framework	25
3.2	Experimental Variables Classification	26
3.3	Sabbionara Gate Venue Advantages	27
3.4	Environmental Management Strategies	27
3.5	Video 1 Stimulus Sequence, Content, and Expected Responses	28
3.6	Unicorn Hybrid Black EEG System Specifications [31]	31
3.7	Movesense ECG System Specifications	32
3.8	Traqbeat Wrist Monitor Specifications[38]	33
3.9	Data Acquisition System Components and Platforms	34
3.10	Informed Consent Components	37
3.11	Pre-Experiment Questionnaire Categories	37
4.1	Recording devices and settings	43
4.2	Median Frequency (MF) Calculation Pipeline	54
4.3	Chronnectomics Analysis Pipeline Overview	56
5.1	Participant Selection Criteria	61
5.2	Lifestyle Factor Distribution	62
5.3	SAM Results Across Experimental Phases (N=33)	65
5.4	Normality test results for ECG features across emotional stimuli using Shapiro-Wilk test ($p > 0.05$ indicates normal distribution)	68

List of Abbreviations

ECG	Electrocardiography
EEG	Electroencephalography
HRV	Heart Rate Variability
MF	Median Frequency
PSD	Power Spectral Density
NG	Neural Gas
SAM	Self-Assessment Manikin
TIE Lab	Transformable Intelligent Environments Laboratory
TUC	Technical University of Crete
RMSSD	Root Mean Square of Successive Differences
SDNN	Standard Deviation of NN intervals
VLF	Very Low Frequency
LF	Low Frequency
HF	High Frequency
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
FDR	False Discovery Rate
PPG	Photoplethysmography
VR	Virtual Reality
ANS	Autonomic Nervous System
CNS	Central Nervous System
SampEn	Sample Entropy

Chapter 1

Introduction

1.1 Motivation and Innovation

Human emotions are made up of a mix of psychological feelings and physical reactions, shaping not only how we feel but also how we act and respond to the world around us [1]. Emotions play a key role in how we think, make decisions, and even in our overall health and well-being [2]. In recent years, there has been a growing need to understand emotions like stress and relaxation using objective, non-invasive methods, especially in fields like neuroscience, biomedical engineering, psychology, and even architecture [3].

However, accurately detecting emotions is still a major challenge. While emotions can be seen in facial expressions, speech, or behavior, measuring them through physiological signals offers a more reliable and unbiased approach. Electroencephalogram (EEG) recordings are particularly valuable because they directly reflect activity from the brain, while electrocardiogram (ECG) signals reveal important information about the body's autonomic responses to emotional states [4–6].

Lately, there has been significant progress in combining different physiological signals to better recognize emotions. For example, studies show that using both EEG and ECG together can boost emotion recognition accuracy, even exceeding 94% for complex emotional tasks [7]. This combined approach overcomes many limitations found in single-modality systems, since each physiological measure reveals different but complementary facets of the emotional responses [8].

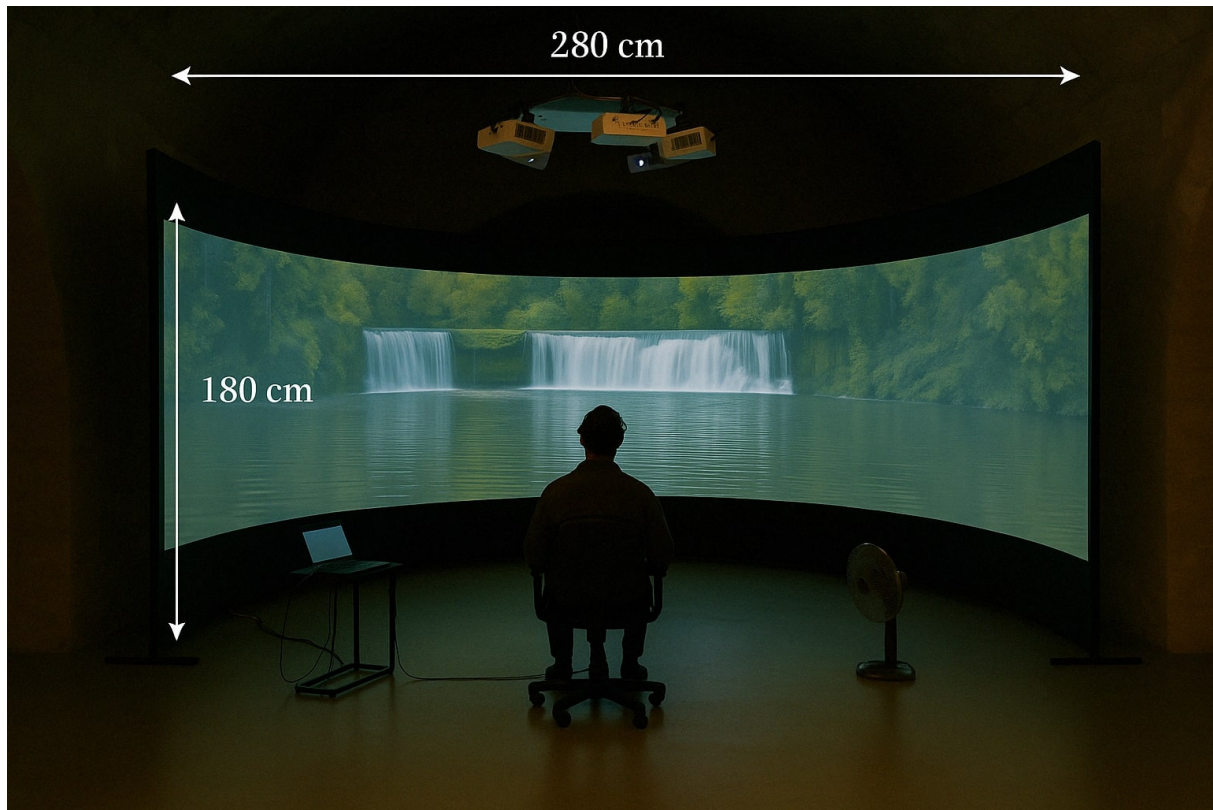


Figure 1.1: Experimental setup at the Sabbionara Gate - Blue Space Stimulus.

What makes this research especially innovative is the choice of experimental environment. Although many studies rely on artificial lab settings or virtual reality, recent work in environmental psychology highlights the powerful effects of natural environments, especially so-called “blue spaces” like rivers, lakes, and the coast—on our mental health and emotional well-being. These natural settings offer unique benefits that virtual or artificial environments simply cannot replicate, including lowering stress and supporting better emotional and cognitive function [9]. Both behavioral data and physiological measures, such as EEG and ECG, confirm these restorative effects [10].

Given these insights and in collaboration with the School of Architecture, this thesis employs an **immersive audiovisual experience in a real blue space**, rather than a virtual one, to trigger emotional responses. The experiment was carried out as a collaboration between the Display Lab (School of Electrical and Computer Engineering) and the Transformable Intelligent Environments Lab (TIE Lab, School of Architecture) at the Technical University of Crete. By combining realistic natural stimuli with multimodal biosignal recording, this setup provides a valid alternative to lab-based or virtual studies [11]. Figure 1.1 shows the special experimental environment at the historic Sabbionara Gate in Chania.

1.2 Research Objectives

The primary objective of this thesis is to develop and evaluate a multi-device system capable of recording and analyzing multimodal physiological signals, specifically, electroencephalography (EEG) and electrocardiography (ECG) from both a chest strap and a wrist-worn device, during exposure to emotionally varied audiovisual stimuli and in an immersive blue space environment. The aim is to investigate how emotions like stress and relaxation are reflected in these physiological signals and to establish reliable methods for detecting and distinguishing different emotional states using this combined approach.

The specific objectives of this research are:

1. **To acquire high-quality multimodal physiological data** from participants during controlled exposure to stressful and calming audiovisual stimuli, utilizing wearable devices, including the Unicorn Hybrid Black EEG system and dual ECG recording systems.
2. **To apply and validate advanced signal processing techniques** for the extraction of meaningful physiological features, including:
 - For EEG signals: median frequency (MF), power spectral density (PSD), band power analysis, sample entropy (SampEn), connectivity analysis and Neural Gas complexity measures [12]
 - For ECG signals: R-peak detection, heart rate variability (HRV) metrics, sample entropy, skewness, and frequency-domain features [15]
 - Statistical validation for both EEG and ECG.
3. **To evaluate the physiological and emotional responses** of the participants within an **immersive projection environment** (real-world blue space simulation), in order to assess the ecological validity and applicability of multimodal emotion recognition in the real-world.

This work brings together the technical precision of biosignal processing with a deep understanding of human emotional experience. The combination of immersive projection and advanced biomedical analysis opens up a wide range of future applications, from healthcare and psychology to environmental and architectural design.

1.3 Thesis Organization

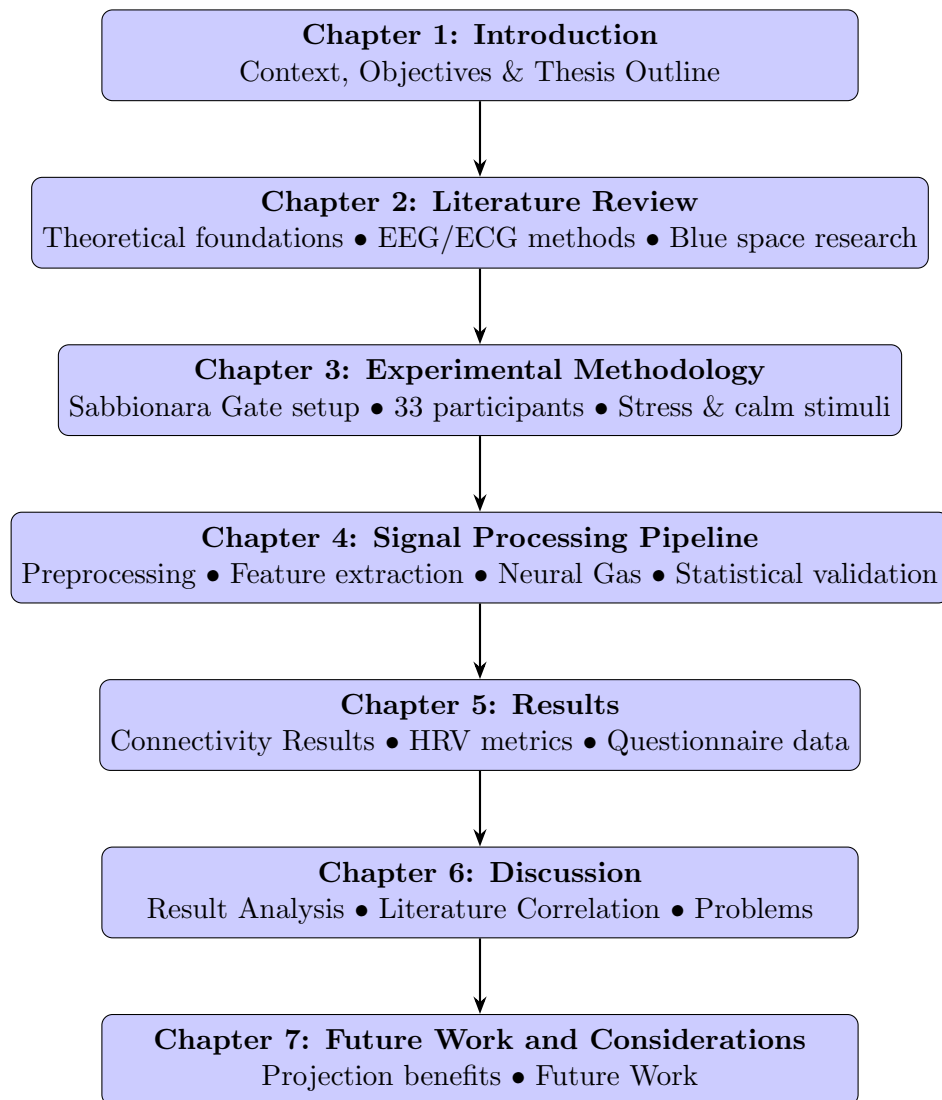


Figure 1.2: Thesis structure: From theoretical foundations through experimental innovation to practical insights

Chapter 2

Literature Review

2.1 Introduction

Research on human emotions using physiological signals is a growing field that brings together neuroscience, psychology, and biomedical engineering. This chapter reviews the main theories and key studies that shaped our experimental design. It highlights recent advances in emotion recognition with multimodal physiological signals, the special role of blue spaces in emotional well-being, and why real-world immersive environments were chosen instead of virtual reality.

2.2 Physiological Correlates of Emotional States

2.2.1 Central Nervous System Responses: EEG

Electroencephalography provides direct measurement of brain activity during emotional processing. The relationship between EEG patterns and emotional states has been extensively documented, with specific frequency bands showing distinct associations with emotional dimensions [5].

Complexity Measures: Beyond spectral analysis, the temporal complexity of EEG signals provides additional discriminative power. For example, sample entropy captures the unpredictability and pattern diversity in neural activity. The implementation of Neural Gas complexity analysis builds on these approaches to capture the topological structure of emotional brain states.

2.2.2 Autonomic Nervous System Responses: ECG and HRV

Heart rate variability derived from ECG provides a non-invasive window into autonomic emotional responses [15]. Time-domain measures (SDNN, RMSSD) indicate the overall variability in heart rate and provide information about parasympathetic activity, while frequency-domain analysis reveals the balance between sympathetic and parasympathetic activation.

Particularly relevant to this study, entropy based measures of HRV have shown sensitivity to emotional states, with higher complexity indicating better emotional regulation [16]. This motivated the inclusion of Sample Entropy alongside traditional HRV metrics to this multimodal analysis.

2.3 Analysis of Blue Spaces, Immersive Projection, and Virtual Reality

“Blue space” refers to natural aquatic environments, oceans, lakes, rivers, and similar settings which many studies have linked to improved mental well-being and stress reduction. The term emerged from research on environmental psychology that recognizes that aquatic environments possess unique properties different from green spaces [9, 17].

Extensive research has documented the mental health benefits of exposure to blue space [18], from improving mental health outcomes, to including reduced psychological stress, lower rates of depression, and improving emotional well-being [24].

In summary, the presence of water in an environment is said to engage the brain in ways that reduce anxiety and foster a calm, reflective state. These theoretical foundations set the stage for empirical research into how exposure to blue spaces, even in short durations, can benefit psychological health. [19]

2.3.1 Virtual Reality versus Immersive Projection in Emotion Research

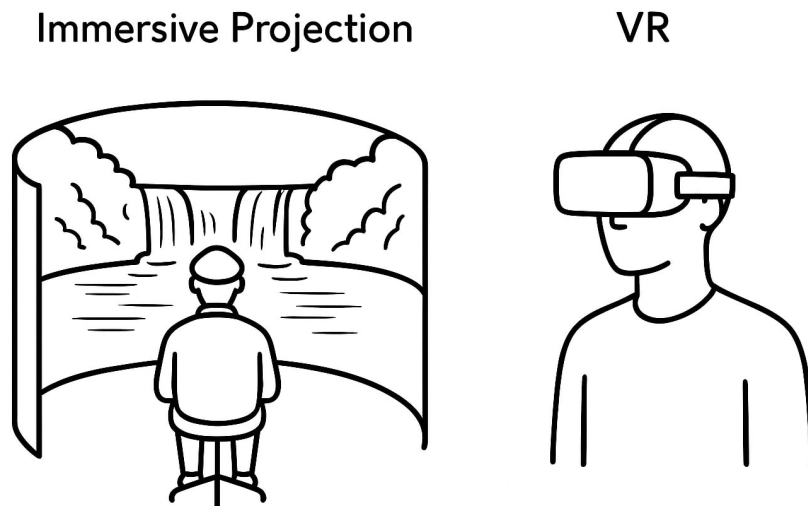


Figure 2.1: Comparison between immersive projection and virtual reality as used in the experimental design.

Comparative Effectiveness of VR and Immersive Projection

Virtual reality (VR) has emerged as a prominent tool in emotion research [20]. However, recent evidence suggests important differences and reactions between VR, immersive projection, and direct natural exposure to emotional responses and therapeutic benefits [19, 21].

Comparative studies reveal that while VR can create emotional responses similar to those from immersive screen-based presentations, there are notable differences in specific emotions such as anger, which tends to be higher in 'real' (outdoor or immersive screen) conditions, while amusement is often elevated in fully virtual settings [22]. In addition, both immersive projection and real environments have stronger effects on stress reduction and mood improvement compared to VR with head mounted displays [14, 23].

Analysis of simulated natural environments shows immediate stress relief and emotional arousal benefits, although the superiority of immersive technologies over standard projection methods remains a great debate, and some studies have not found significant differences between head-mounted displays and computer screens in physiological measures [13].

Rationale for Curved Screen Immersive Projection

The decision to utilize immersive projection of a curved screen rather than VR technology was based on practical and methodological considerations, specifically:

- Technical and Measurement Advantages: Curved screens improve visual exploration and reduce edge distortion compared to flat monitors, which is especially helpful for peripheral vision tasks. Recording EEG in VR can be challenging since headsets introduce motion artifacts and electromagnetic noise, but the projection setup largely avoids those issues [22].
- Enhanced Blue Space Presentation: For the therapeutic blue space content, the curved screen format provided an immersive visual field that effectively simulated the expansive quality of natural blue environments. Blue spaces have demonstrated significant mental health benefits and the projection setup aimed to maximize these effects [9, 19].
- Participant Comfort: VR headsets often cause simulator sickness, especially in sessions over 15 minutes whereas the curved projection lets people move naturally without feeling any discomfort. [13].
- Experiment Requirements: While Video 1 included varied emotional stimuli (including two beach/sea segments), Video 2 specifically required the creation of a calming blue space atmosphere. Research demonstrates that curved and immersive environments feel more inviting and less threatening, with people more likely to linger in such spaces due to evolutionary safety associations [24].
- Contextual and Infrastructural Opportunity: The availability of the large curved screen installation at the Sabbionara Gate [30], a unique architectural site in Chania, provided an ideal platform for the immersive projection.



Figure 2.2: Immersive projection environment used for audiovisual stimulus presentation.

2.4 Multimodal Emotion Recognition

2.4.1 Advantages of Multimodal Approaches

Emotion recognition using physiological signals has traditionally relied on single modalities such as EEG or ECG. However, these systems alone exhibit limitations. EEG provides good temporal information and is highly sensitive to rapid changes in emotional state, yet suffers from limited spatial resolution and is vulnerable to artifacts caused by eye movements, muscle activity or electrode detachment. In contrast, ECG-based approaches are comparatively stronger to movement artifacts and offer valuable insights into autonomic nervous system (ANS) responses. However, ECG lacks the ability to capture the subtle central nervous system (CNS) dynamics underlying cognitive-emotional processing.

Multimodal emotion recognition systems, which include both EEG and ECG, benefit greatly from the complementary strengths of each of these signals and can capture a more holistic and accurate representation of emotional states [8, 25].

Many studies underscore these advantages [1] by demonstrating that a fusion model, combining EEG and ECG features achieve 95.95% accuracy, compared to 71–77% for single-modality systems.

Chapter 3

Experimental Methodology

Chapter Overview

This chapter outlines the experimental design, equipment configuration, and methodological procedures for investigating how people respond physiologically to immersive audiovisual experiences.

The experimental approach built upon established work in affective computing and emotion recognition [2]. We also drew insights from recent advances in emotion recognition research that employ biosignals and machine learning techniques [25, 28].

The chapter details all aspects of the experimental process, including participant preparation, informed consent procedures, device setup for EEG and ECG recording, all the protocols used and the video presentation methodology.

3.1 Participants

Participants were recruited through an open call that was announced via posters and social media platforms, primarily focusing on students and staff at the Technical University of Crete. Those interested in participating filled out an online screening questionnaire through Google Forms, where they shared basic demographic details and indicated their availability to take part.

Based on this study’s goals, only **right-handed individuals** were included. This decision follows the approach taken by many previous studies, which limit participation to right-handers to minimize variability in emotional processing that stems from differences in brain lateralization [2, 27]. Handedness is known to influence which brain hemisphere is dominant, especially during emotional processing tasks, and this can significantly impact both EEG readings and other physiological responses.

Following the participant selection, individual experimental sessions were scheduled based on participant availability, and each participant completed the experimental procedure according to a predefined timetable.

Further details regarding participant exclusion criteria and the final sample composition are presented in Chapter 5.

3.2 Experimental Design

3.2.1 Research Hypotheses Framework

The study was designed to test three complementary hypotheses, each addressing different aspects of emotional response to immersive audiovisual stimuli.

Table 3.1: Research Hypotheses Framework

Hypothesis Type	Description	Expected Outcomes
Primary	Exposure to stress-inducing visual content results in measurable changes in EEG and ECG patterns compared to baseline and relaxation states	Significant differences in neural and cardiac metrics
Secondary	Blue space environments induce physiological markers of relaxation and stress reduction	• Increased alpha power, decreased beta power in EEG • Increased HRV and parasympathetic activity • Reduced complexity measures
Tertiary	Multimodal analysis combining EEG and ECG provides superior discrimination between emotional states	Enhanced classification accuracy versus single-modality approaches

3.2.2 Variable Classification

Table 3.2: Experimental Variables Classification

Variable Type	Components
Independent Variables	• Stimulus Type: Stress-inducing vs. calming content • Blue Space Presence: Present vs. absent • Temporal Position: Sequential time points in experimental flow
Dependent Variables	• EEG Measures: Median frequency, PSD, entropy, complexity • ECG Measures: Heart rate, HRV parameters, R-R interval statistics • Subjective Ratings: SAM scores (valence, arousal, dominance)
Control Variables	• Environmental: Lighting, temperature, noise levels • Temporal: Sessions conducted 10:00-18:00 • Physiological: No caffeine 2h prior, adequate sleep

3.3 Experimental Environment

3.3.1 Location: Sabbionara Gate Historical Venue

The Sabbionara Gate (Πύλη Σαμπιονάρα), a historical monument in the Koum Kapi area of Chania, Crete, was chosen for several strategic reasons that enhanced both the experimental validity and the participants' experience.



Figure 3.1: The Sabbionara Gate experimental location located in Chania, Crete. [30]

Strategic Location Benefits

Table 3.3: Sabbionara Gate Venue Advantages

Advantage	Description	Impact
Historical Significance	Only surviving Venetian gate (1538-1590)	Enhanced ecological validity and cultural relevance
Acoustic Properties	Natural sound insulation from stone architecture	Optimal audio delivery, minimal interference
Spatial Dimensions	Approx. 137m ² interior floor area	Suitable for immersive projections and experimental setup
Accessibility	Walking distance from city center	Facilitated participant recruitment and attendance

Immersive Display System



Figure 3.2: Interior view of the Sabbionara Gate. [30]

Environmental Challenges & Solutions

Table 3.4: Environmental Management Strategies

Challenge	Mitigation Strategy
Temperature Control	• 2 industrial fans • Cooler hour scheduling
Humidity Variation	• Opening Doors
Limited Natural Light	• Artificial lighting • Blackout curtains for projection

3.4 Stimulus Materials

3.4.1 Video 1: Mixed Emotional Content Sequence

The first video was designed to elicit contrasting emotional states through a carefully sequenced combination of stressful and calming content.

Table 3.5: Video 1 Stimulus Sequence, Content, and Expected Responses

Stimulus	Content	Duration	Expected Response	Source
1. Beach 1	Calm ocean waves	0:30 min	Relaxation baseline	YouTube [32]
2. Shark Attack	Underwater shark encounter (first-person)	2:00 min	Fear, anxiety, sympathetic activation	YouTube [33]
3. Rollercoaster	High-speed coaster with drops/inversions	2:00 min	Excitement, arousal, vestibular stimulation	YouTube [34]
4. Nature Valley	Peaceful valley with gentle breeze	0:30 min	Mid-sequence recovery (calm)	YouTube [35]
5. Night Forest	Dark forest walk, limited visibility	1:00 min	Tension, vigilance, uncertainty	YouTube [36]
6. Beach 2	Return to beach environment	0:30 min	Final relaxation recovery	YouTube [32]

Total Duration: 6.5 minutes content + 1 minute transitions = 7.5 minutes



(a) Stimulus 1 – Beach 1 (Relaxation)



(b) Stimulus 2 – Shark Attack (Fear)



(c) Stimulus 3 – Rollercoaster (Excitement)



(d) Stimulus 4 – Nature Valley (Recovery)



(e) Stimulus 5 – Night Forest (Tension)



(f) Stimulus 6 – Beach 2 (Recovery)

Figure 3.3: Snapshots from the six video stimuli used in the experiment.



(a) Participant viewing Stimulus 1 – Beach 1



(b) Participant viewing Stimulus 2 – Shark Attack



(c) Participant viewing Stimulus 3 – Roller-coaster



(d) Participant viewing Stimulus 4 – Nature Valley



(e) Participant viewing Stimulus 5 – Night Forest



(f) Participant viewing Stimulus 6 – Beach 2

Figure 3.4: Snapshots of real participants during the experiment, watching the six video stimuli inside the immersive projection space.

3.4.2 Video 2: Blue Space Immersion Protocol

The second video featured continuous calming blue space content designed to induce relaxation and restoration.

Structure: 30s baseline + $4 \times$ 2-minute blue space environments + 5s transitions = 8.75 minutes

3.5 Equipment

3.5.1 EEG Recording System: Unicorn Hybrid Black

The EEG data acquisition was performed using the Unicorn Hybrid Black system [31](g.tec medical engineering GmbH), a wireless 8-channel EEG headset specifically designed for research applications. This system follows modern approaches to emotion detection using EEG signals, providing adequate spatial resolution for emotion recognition while maintaining participant comfort.



(a) EEG headset preparation with conductive gel application



(b) Participant wearing the Unicorn EEG headset during experiment

Figure 3.5: EEG Recording System Setup and Application

Table 3.6: Unicorn Hybrid Black EEG System Specifications [31]

Specification	Value	Purpose
Channels	8 active electrodes	Spatial coverage following 10-20 system
Sampling Rate	250 Hz	Adequate for EEG analysis
Resolution	24-bit ADC	High precision signal acquisition
Connectivity	Bluetooth 2.1	Wireless recording
Battery Life	3 hours continuous	Full experimental session coverage
Weight	65g (headset only)	Participant comfort maintenance

Electrode Placement Protocol [37]

Following the International 10-20 system for standardized electrode positioning, consistent with established emotion recognition protocols:

- **Active Electrodes:** Fz, C3, Cz, C4, Pz, PO7, Oz, PO8
- **Reference Electrode:** Left earlobe
- **Ground Electrode:** Right earlobe

3.5.2 ECG Recording Systems

Two complementary ECG systems were employed to ensure data reliability and provide redundancy in cardiac monitoring. This dual-system approach enhances the robustness of physiological data collection, following best practices in multimodal emotion recognition [25].

Primary System: Movesense Medical Sensor

The primary cardiac monitoring was conducted using the Movesense Medical Sensor, a research-grade chest-worn device.



Figure 3.6: Movesense ECG chest strap positioning between 3rd and 4th ribs for optimal R-wave detection[29]

Table 3.7: Movesense ECG System Specifications

Feature	Specification	Advantage
Placement	Chest strap (3rd-4th ribs)	Optimal R-wave detection
Sampling	512 Hz $\rightarrow$ 250 Hz	Medical-grade accuracy
Connectivity	Bluetooth Low Energy	Low power consumption
Electrodes	Dry textile electrodes	Minimal skin preparation

Secondary System: Traqbeat Wrist Monitor



Figure 3.7: Traqbeat wrist monitor placement for backup monitoring and movement detection [38]

Table 3.8: Traqbeat Wrist Monitor Specifications[38]

Feature	Specification	Purpose
Technology	Optical PPG (pulse waveform) + 3-axis accelerometer	Heart rate tracking and movement-artifact detection
Sampling Rate	PPG: 25–100Hz Accel.: 50–200Hz	Variable fidelity: low-power baseline, high fidelity for accurate waveform capture
Placement	Wrist (dominant preferred)	Unobtrusive continuous monitoring

3.5.3 Data Acquisition & Synchronization

Hardware Components

Table 3.9: Data Acquisition System Components and Platforms

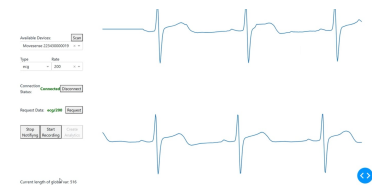
Component	Model/Type	Function
EEG Software	Unicorn Suite (Windows 11)	EEG recording with real-time visualization ($\pm 500\mu\text{V}$ scaling), bandpass filtering (0.1Hz), notch filtering (50Hz), impedance monitoring, and LSL streaming
ECG Primary	Movesense App (Raspberry Pi 4, adapted from [26])	Real-time ECG signal acquisition and visualization, primary cardiac monitoring using a medical device
ECG Secondary	Traqbeat with custom Python script (Windows 11)	Backup heart rate monitoring and movement artifact detection via Python
Synchronization Hub	Raspberry Pi 4 Model B (4GB) and Windows 11 Terminals	Manual synchronization using flagging mechanism: At video start, the operator manually entered a '1' command into the terminal on both Raspberry Pi and Windows 11 systems to simultaneously set True flags on all devices, enabling timestamp alignment
Questionnaire Platform	Paper Form	Manual questionnaire completion by participants in real-time



(a) Raspberry Pi 4 (For the Movesense App)



(b) Windows 11 (EEG + Traqbeat Scripts)



(c) Movesense Showcase App Interface [26]

Figure 3.8: Main computing platforms and software used for data acquisition and synchronization.

3.6 Experimental Procedure

3.6.1 Pre-Experiment Phase (15 minutes)

1. Welcome & Orientation (5 minutes)

- **Venue Introduction:** Historical background of the Sabbionara Gate.
- **Study Overview:** General purpose of the experiment.
- **Q&A Session:** Clarifications regarding the procedure and participants' rights.

2. Device Setup & Consent Process (10 minutes)

Summary of Steps:

- **Device Placement:** EEG headset and ECG devices were carefully placed on participants (*see Sections 3.6.1 and 3.6.1*).
- **Informed Consent:** Participants signed the consent form and were briefed on the recording process and data protection (*see Table 3.10*).
- **Pre-Experiment Questionnaire:** Participants completed the demographic and lifestyle questionnaire (*see Table 3.11*).
- **Baseline Self-Assessment:** Initial self-assessment questionnaire to record emotional state before video exposure (*see Section 3.6.1*).

EEG Preparation Protocol



(a) Conductive gel application to electrode sites



(b) Headset positioning and electrode adjustment

Figure 3.9: EEG Preparation Process

1. **Scalp Preparation:** Alcohol wipe cleaning
2. **Conductive Gel:** Application to electrode sites
3. **Headset Positioning:** Unicorn Hybrid Black adjustment
4. **Signal Quality:** Real-time verification
5. **Comfort Assessment:** Participant feedback

ECG Setup Protocol



(a) Placement of the Movesense ECG chest strap on the participant's torso for primary cardiac signal recording.



(b) Placement of the Traqbeat wrist monitor on the participant's dominant wrist for backup heart rate monitoring.

Figure 3.10: ECG Preparation Process

1. **Chest Strap:** Movesense positioning (3rd-4th ribs)
2. **Wrist Monitor:** Traqbeat placement on dominant wrist
3. **Signal Verification:** Clear R-peaks and HR detection
4. **Synchronization:** Cross-device timing check
5. **Movement Test:** Artifact assessment

Ethics Approval & Compliance

The study received formal ethics approval from the Ethics and Deontology Committee of the Technical University of Crete (approval No. 71/21-05-2024). The study was carried out according to the ethical guidelines of the Technical University of Crete. Data collection and storage procedures followed the General Data Protection Regulation (GDPR), ensuring anonymity and confidentiality. Personally identifiable information was stored separately from the research data and accessible only to the principal investigators.

Table 3.10: Informed Consent Components

Consent Component	Details
Ethics Approval	Technical University of Crete Ethics and Deontology Committee (Approval No. 71/21-05-2024)
Procedure	~20 minutes of video viewing with simultaneous biosignal recording using a multisensory system
Recording	Optional audio and/or video recording of the procedure for documentation and transcription purposes
Media Usage	Optional consent for anonymized use of photos and videos in scientific publications, participants waive the right to review or approve final materials
Data Protection	Only the principal investigator has access to identifying data
Voluntary Participation	Participation is fully voluntary, participants may withdraw at any time or skip any procedure/question without penalty
Future Contact	Optional consent for potential contact and follow-up research studies

Table 3.11: Pre-Experiment Questionnaire Categories

Category	Variables
Demographics	Sex, age, handedness
Lifestyle Factors	Exercise today, sleep quality, caffeine/alcohol consumption, smoking habits, gaming experience
Health & Stress	Current stress (1–10), monthly stress average, existing medical conditions, medications
Phobia Screening	Public speaking, heights, enclosed spaces, sea/ocean, sharks, clowns, other specific fears

Baseline Recording & Assessment

Emotional State Baseline (Pre-Experiment SAM)

The Self-Assessment Manikin (SAM) pictorial assessment scale was used before and between the two videos, to establish baseline emotional state across three dimensions.

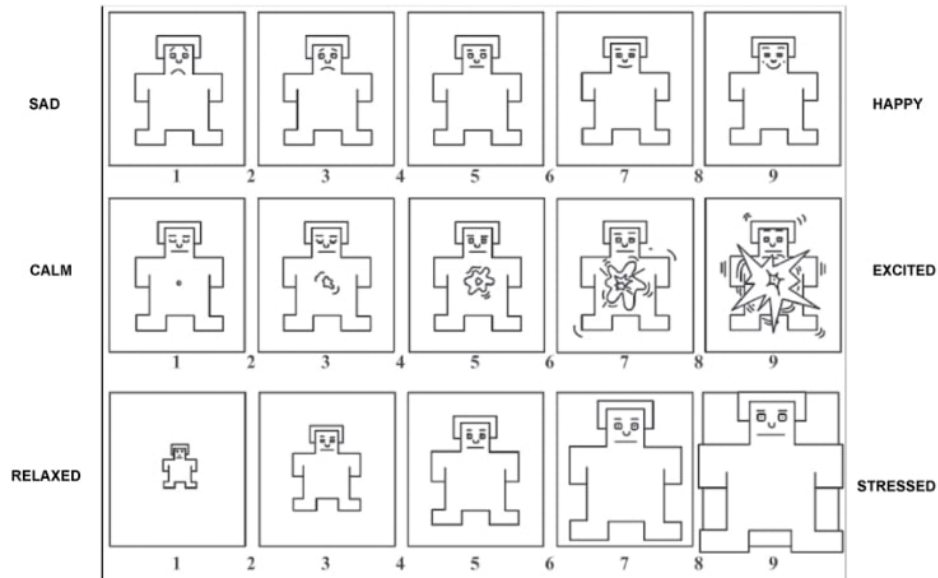


Figure 3.11: Self-Assessment Manikin (SAM) pictorial scales used for emotional assessment.

SAM Dimensions:

- **Valence:** Sad (1) ↔ Happy (9)
- **Arousal:** Calm (1) ↔ Excited (9)
- **Stress Level:** Relaxed (1) ↔ Stressed (9)

3.6.2 Experimental Phase (~20 minutes)

1. **Video 1 Viewing:** Participants watched the first video while EEG and ECG signals were recorded (*See 3.6.2*).
2. **Post-Video 1 Self-Assessment:** Participants completed a short self-assessment questionnaire to report their emotional state after Video 1(*See 3.6.2*).
3. **Video 2 Viewing:** Participants then watched the second video (~8.5 minutes) under the same recording conditions(*Same as Video 1 3.6.2*).
4. **Post-Video 2 Self-Assessment:** Participants completed a second self-assessment, including additional questions about their overall experience:
 - Most anxiety-inducing video (selecting from Video 1 stimuli).
 - Most calming video (selecting from Video 2 stimuli).



Figure 3.12: Experimental setup along with the participant seated at the center with EEG and ECG devices.

Video (7.5 minutes)

Before the video began, participants were instructed to watch the screen attentively, fully immerse themselves in the content, minimize unnecessary movements while remaining comfortable, and were reminded that there were no right or wrong responses expected from them.

During the video presentation, automatic event markers were triggered at each stimulus transition to facilitate later analysis. Continuous EEG and ECG recordings were performed throughout the entire video, with real-time monitoring by the research team from an adjacent room to ensure data quality. No interruptions occurred during the video unless an emergency situation arose.

3 minutes assessment

Immediately after the video ended, participants completed a post-video assessment lasting approximately three minutes. This included a Self-Assessment Manikin (SAM) rating to capture their current emotional state, along with specific questions evaluating the video stimuli. They were also asked to identify the most terrifying clip, report any physical discomfort experienced, and provide a brief free-text description of their emotional reactions. A short two-minute intermission was provided. During this break, participants remained seated to maintain the correct positioning of the biosignal recording equipment and they were also offered hydration.

3.6.3 Post-Experiment Phase (5 minutes)

- **Device Removal & Cleanup:** All biosignal recording devices were removed, and participants' skin was cleaned.
- **Session Completion:** Participants were thanked for their participation and dismissed.

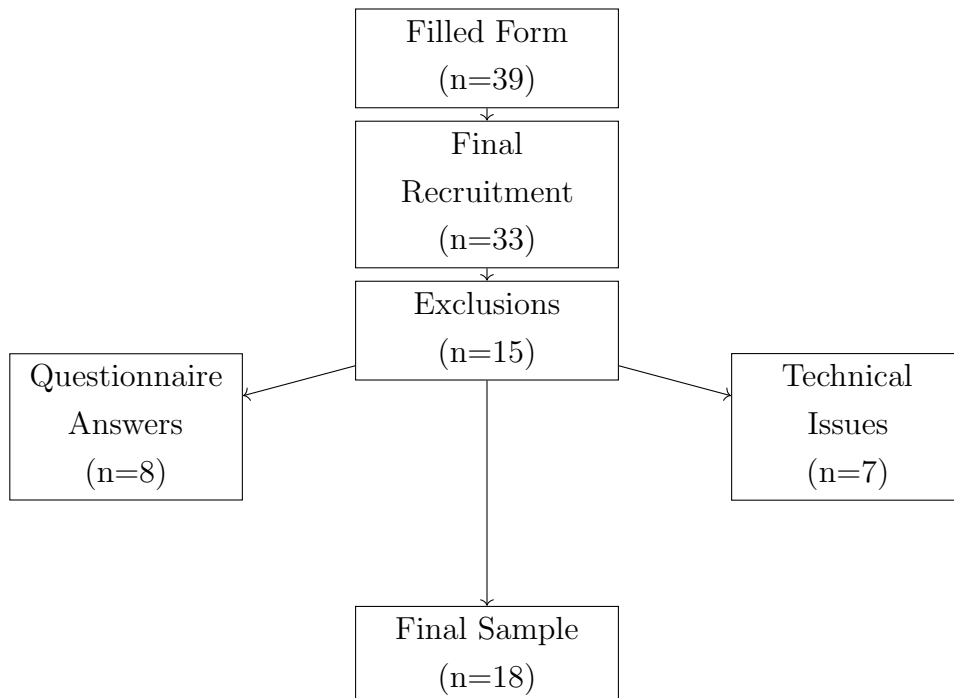
Chapter 4

Signal Processing and Analysis Methods

4.1 Dataset Acquisition

4.1.1 Participant Selection and Exclusion Criteria

Prior to any signal-processing or artifact-removal steps, we collected raw EEG, ECG and questionnaire data under controlled experimental conditions. The participant recruitment and selection process followed a systematic approach to ensure data quality and experimental validity. Below we summarize the participants, hardware, stimuli, and file organization.



1. **Initial Recruitment:** A total of 39 participants completed the initial consent forms and expressed interest in participating in the study.
2. **Handedness:** Only right-handed participants were retained for the study, reducing the sample from 39 to 33 participants. This criterion was implemented to ensure neurophysiological homogeneity in the dataset.
3. **Medical History Exclusion:** Participants were excluded if they reported taking any medications affecting neurological or psychological states, including:
 - Anxiety medications
 - Depression medications
 - Dyslexia-related medications
 - Other psychoactive substances

This information was collected through pre-experimental questionnaires.

4. **Technical Device Validation:** Participants were excluded if any of the three recording devices experienced technical failures during data collection:
 - *Unicorn EEG Headset:* Exclusions due to incomplete channel connections or poor electrode contact
 - *Raspberry Pi:* Device disconnections during recording sessions caused by poor contact with the wrist
 - *Movesense ECG:* System shutdowns caused by extreme ambient temperature conditions
5. **Final Sample:** After applying all exclusion criteria, the final dataset consisted of 18 healthy participants with reliable, complete physiological recordings suitable for statistical analysis.

4.1.2 Experimental Protocol

Each participant watched two videos (parts 1 and 2) containing alternating stress-inducing and calming scenes:

1. *Video 1:* alternating stress / calm stimuli
2. *Video 2:* blue spaces / calm stimuli

Videos were segmented into predefined epochs (e.g. beach, shark attack, rollercoaster, nature, night walk) totaling 6–8 minutes per video. Participants completed a brief pre- and post-questionnaire (demographics, sleep quality, stress levels, phobias, etc.) immediately before and after each session.

4.1.3 Hardware & Recording Settings

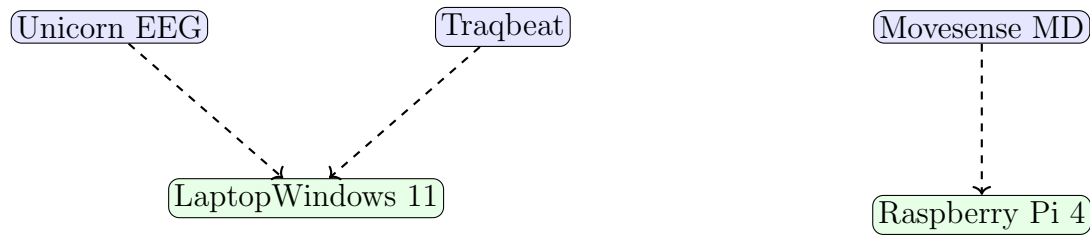


Figure 4.1: Data acquisition setup: EEG via Unicorn headset into a Windows laptop, wrist and chest-worn ECG devices into a Raspberry Pi.

Table 4.1: Recording devices and settings

Modality	Device	Specifications
EEG	Unicorn Hybrid Black	Data in <code>part1.csv</code> , <code>part2.csv</code> .
ECG (Dual)	Traqbeat (wrist) Movesense (chest strap)	Dual-device for cross-validation.
Questionnaires	Paper Form	Single CSV.

Dual ECG Device Recording System

The two complementary devices provided several benefits:

- **Redundancy:** Backup measurements in case of device failure.
- **Cross-validation:** Comparison between chest and wrist-based measurements.
- **Motion artifact detection:** Wrist accelerometer data helped identify movement artifacts and track temperature changes.

4.1.4 Raw Data Organization

- *Directory structure:*

```
/data/  
  EEG/  
    sub-01_part1.csv  
    sub-01_part2.csv  
    ...  
  ECG/  
    Traqbeat_sub-01_part1.csv  
    Traqbeat_sub-01_part2.csv  
    Movesense_sub-01_part1.csv  
    Movesense_sub-01_part2.csv  
    ...  
  Questionnaires.csv
```

- **Total files:**

- EEG: 36 files ($18 \text{ subjects} \times 2 \text{ parts/videos}$)
- ECG (Traqbeat + Movesense): 72 files (18×4)
- Questionnaires: 1 Excel file
- *Grand total:* 109 files

4.2 ECG Preprocessing

Raw Signal Characteristics

The raw ECG signals from both devices exhibited distinct characteristics as shown in Figure 4.2.

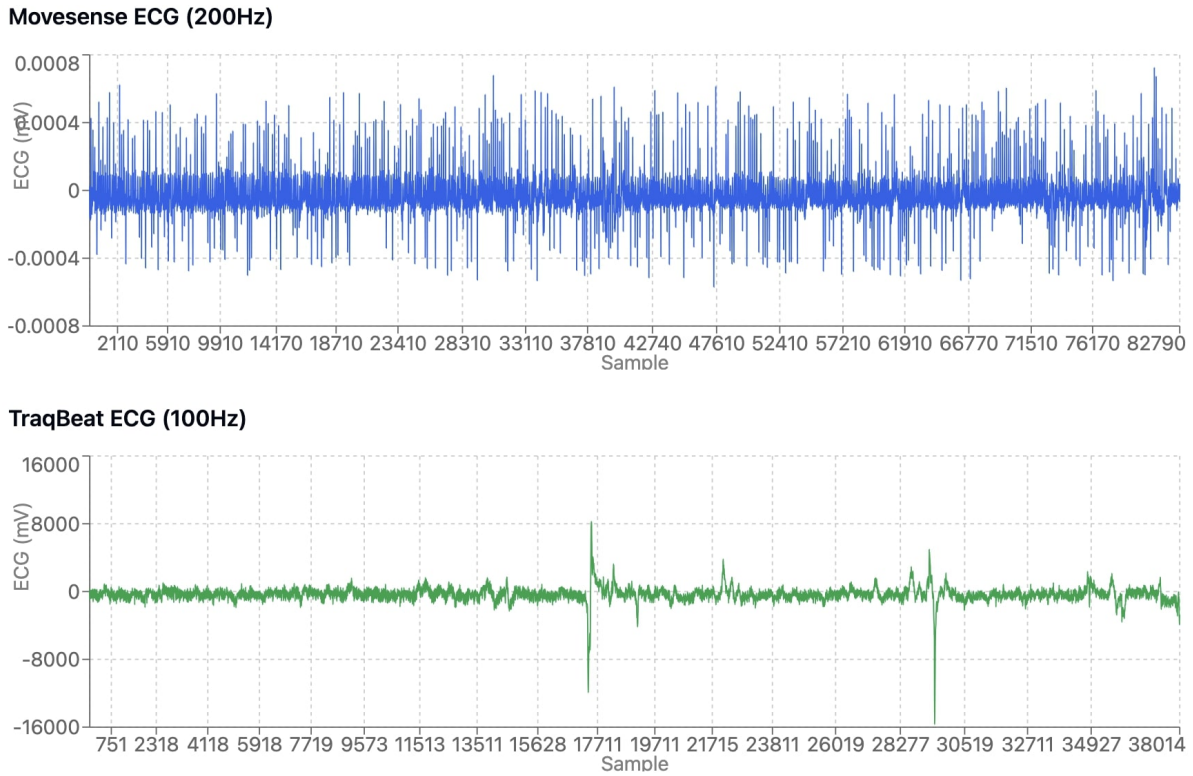


Figure 4.2: Comparison of raw ECG signals from and Movesense (top) and Traqbeat (bottom) devices for the same participant.

Device Selection for Analysis

After initial comparison and validation, **Movesense was selected as the primary device** for all subsequent ECG analysis based on:

1. **Superior Signal Quality:** Clearer R-peak detection with fewer false positives
2. **Consistent Placement:** Chest position less affected by arm movements during video viewing

Traqbeat data was retained for cross-validation and motion artifact detection purposes.

Stimulus-Specific Signal Processing Implementation

Following the device selection of Movesense for primary analysis, the signal processing pipeline was adapted to handle stimulus-specific segmentation and analysis. Rather than processing the entire ECG recording as a single continuous signal, the methodology was designed to extract and analyze each emotional stimulus independently, enabling precise assessment of cardiac responses to individual emotional provocations.

Temporal Segmentation Strategy The complete ECG recording was segmented according to predefined stimulus time windows, as illustrated in Figure 4.3. For Video 1, six distinct emotional stimuli were identified with their corresponding temporal boundaries: Beach1 (0–30s), Shark Attack (35–155s), Rollercoaster (160–280s), Nature (285–315s), Night Walk (320–380s), and Beach2 (385–415s).

This approach enabled direct comparison across all of the stimuli. We applied the designed preprocessing pipeline to both: (1) segmented data (per stimulus) and (2) the whole dataset. The same stimulus-specific processing methodology was applied to both Video 1 and Video 2 sessions.

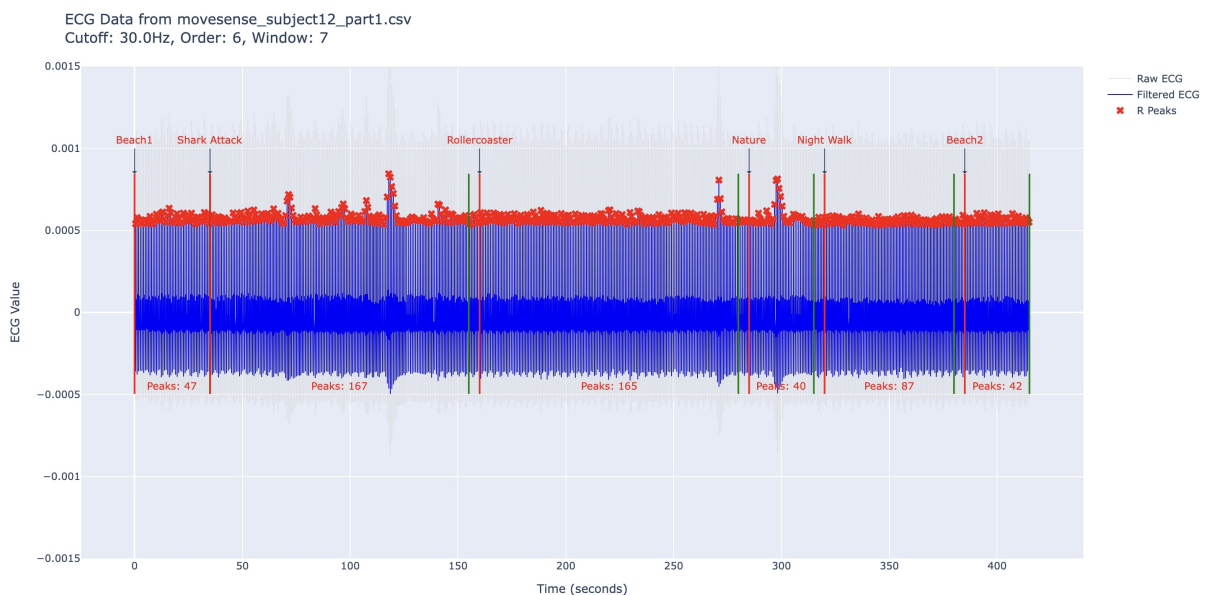


Figure 4.3: Complete ECG signal processing for Video 1: Beach1 (pink), Shark Attack (orange), Rollercoaster (green), Nature (blue), Night Walk (purple), and Beach2 (light pink). Red dots mark detected R-peaks across the entire 414s recording.

4.2.1 ECG Signal Processing and Analysis

Heart rate variability (HRV) analysis has become a cornerstone method for assessing autonomic nervous system responses to emotional stimuli. This ECG processing pipeline was designed to extract reliable cardiac features that could differentiate between stress-inducing and calming audiovisual experiences. The methodology builds upon established HRV analysis frameworks while incorporating modern signal processing techniques optimized for emotion recognition applications.

4.2.2 Data Acquisition

ECG data were collected from 18 participants using Movesense medical-grade sensors positioned on the chest, recording at 200 Hz sampling frequency. The experimental protocol included two video sessions: Video 1 presented six distinct emotional stimuli (Beach1, Shark Attack, Rollercoaster, Nature, Night Walk, Beach2) with durations ranging from 30 to 120 seconds, while Video 2 featured four blue space environments of similar duration. This design allowed us to capture cardiac responses across a spectrum of emotional states.

4.2.3 Signal Preprocessing Pipeline

The preprocessing approach followed established practices for HRV analysis [39] while adapting techniques from recent emotion recognition studies [40, 41]. The multi-stage pipeline was designed to preserve physiologically relevant information while removing artifacts that could compromise subsequent analysis.

Stage 1: Noise Reduction

Raw ECG signals first underwent fourth-order Butterworth lowpass filtering with a 30 Hz cutoff frequency. This choice was motivated by the fact that QRS complex energy is predominantly contained below 30 Hz [40]. The filter was implemented using zero-phase filtering (`filtfilt()`) to prevent phase distortion that could affect peak timing accuracy.

Stage 2: Signal Smoothing

Following the initial filtering, a 7-sample moving average filter was applied to further reduce baseline fluctuations and high-frequency noise. The 35-millisecond window (7 samples at 200 Hz) was chosen and even though this window length is shorter than typical R-peak durations (40-120 ms), it ensures that cardiac features remain sharp while effectively smoothing residual high-frequency artifacts that may exist after the initial Butterworth filtering stage. [42].

Stage 3: Amplitude Normalization

Finally, amplitude normalization was performed by dividing the filtered signal by its standard deviation.

4.2.4 R-Peak Detection

Given that R-peak identification forms the basis of all HRV computations, an adaptive strategy was employed to ensure accurate detection to the specific signal morphology of each participant, following protocols already established in clinical HRV literature [43, 44].

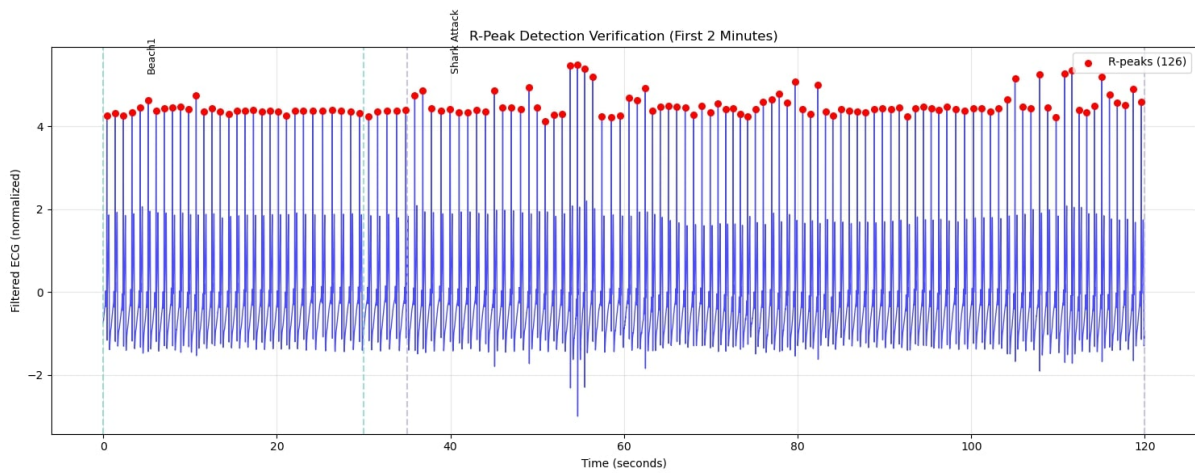


Figure 4.4: R-peak detection verification on filtered ECG, detected R-peaks (red dots).

Adaptive Threshold Calculation

The detection threshold was calculated as the signal mean plus 0.3 times the signal standard deviation. This adaptive approach ensures good performance across participants with different signal amplitudes and baseline characteristics, while maintaining sensitivity to true R-peaks.

Physiological Constraints

To prevent false detections, we enforced a minimum inter-peak distance of 500 milliseconds, corresponding to a maximum physiologically plausible heart rate of 120 beats per minute during experimental conditions.

Validation

R-peak detection accuracy was validated through manual verification on 20% of recordings. Cross-device comparison between Movesense and Tracbeat sensors showed strong correlation, confirming the reliability of the algorithm.

4.2.5 R-R Interval Extraction and Quality Control

R-R intervals were calculated as temporal differences between consecutive R-peak occurrences. However, even with peak detection R-R interval series can contain artifacts requiring systematic identification and removal.

Physiological constraints (applied in all methods): R-R intervals outside the range of 0.33 to 1.5 seconds were removed, corresponding to heart rates between 40 and 180 beats per minute.

Sudden change detection: Intervals that differed by more than 20% from the local median R-R interval were identified and removed as well, since these typically indicate missed or false R-peak detections.

Statistical outlier detection: Intervals with absolute modified z-scores exceeding 3.5 were removed.

4.2.6 Heart Rate Variability Metrics

From the obtained and cleaned R-R interval series, we extracted a comprehensive set of HRV metrics representing different aspects of cardiac autonomic control. The selection was guided by established clinical standards [39] and recent emotion recognition literature [16].

Time-Domain Metrics

Mean R-R Interval: The average cardiac cycle length, reflecting baseline heart rate and overall autonomic tone.

$$\overline{RR} = \frac{1}{N} \sum_{i=1}^N RR_i \quad (4.1)$$

SDNN: Standard deviation of normal-to-normal intervals, indicating overall heart rate variability and the combined influence of sympathetic and parasympathetic activity.

$$SDNN = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (RR_i - \overline{RR})^2} \quad (4.2)$$

Complexity and Distribution Metrics

Sample Entropy: A regularity statistic quantifying the complexity and predictability of the R-R interval time series. Higher entropy values indicate greater irregularity and complexity, often associated with healthy cardiac function and adaptive capacity [45].

Skewness: Measures the asymmetry of the R-R interval distribution, providing insight into the heart rhythm's tendency toward shorter or longer intervals during different emotional states.

$$\text{Skewness} = \frac{\frac{1}{N} \sum_{i=1}^N (RR_i - \overline{RR})^3}{\left(\frac{1}{N} \sum_{i=1}^N (RR_i - \overline{RR})^2 \right)^{3/2}} \quad (4.3)$$

Power: The variance of the R-R interval series, representing the total power of heart rate fluctuations and overall variability magnitude.

$$\text{Power} = \frac{1}{N-1} \sum_{i=1}^N (RR_i - \overline{RR})^2 \quad (4.4)$$

4.2.7 ECG Statistical Analysis

The ECG analysis focused on heart rate variability (HRV) metrics extracted from R-R interval data across all five emotional stimuli: Shark Attack, Rollercoaster, Nature, Night Walk, and Beach2. A statistical approach was implemented, to ensure appropriate test selection and control for multiple comparisons between the given data.

Normality Assessment

Prior to conducting comparative statistical tests, we assessed the normality of each ECG feature (Power, Entropy, Skewness and SDNN) across all stimuli using the Shapiro-Wilk test [60]. This test is particularly suitable for smaller sample sizes and provides reliable assessment of distributional assumptions required for parametric statistical methods.

The Shapiro-Wilk test was applied to each feature within each stimulus condition separately, allowing the assessment of each stimulus. A threshold of $p > 0.05$ was used to determine normal distribution, consistent with standard statistical practice.

Parametric Analysis: One-way ANOVA was used when assumptions were met, with effect sizes quantified using eta-squared (η^2).

Statistical Test Selection

Based on the normality assessment results, we employed both parametric and non-parametric statistical tests.

- **Parametric Tests:** When both groups in a comparison exhibited normal distributions, parametric tests were applied. Paired t-tests were used for within-subject comparisons with equal sample sizes, while independent t-tests were employed for between-group comparisons [61, 63].
- **Non-parametric Tests:** When either group demonstrated non-normal distributions, non-parametric tests were applied. The Wilcoxon signed-rank test was used for paired samples, and the Mann-Whitney U test was applied for independent samples [62].

FDR Comparison Correction

Given the nature of the analysis involving multiple stimulus pairs and ECG features, we applied False Discovery Rate (FDR) correction using the Benjamini-Hochberg method [64]. The FDR approach was selected over methods like Bonferroni correction as it provides better statistical power while maintaining appropriate control of false discoveries in exploratory physiological research.

The FDR correction was applied to all p-values obtained from the statistical comparisons, with an alpha level of 0.05.

Correction Scope:

- **ECG Analysis:** FDR correction applied to 40 statistical tests across 10 stimulus pairs and 4 HRV features.

Effect Size Calculation

To complement significance testing, effect sizes were calculated for all comparisons to assess significance. Cohen's d was computed for parametric tests, while effect size r was calculated for non-parametric tests. Effect size interpretation followed established conventions: small ($d = 0.2$, $r = 0.1$), medium ($d = 0.5$, $r = 0.3$), and large ($d = 0.8$, $r = 0.5$) effects.

4.3 EEG Signal Processing Pipeline

The EEG signal processing pipeline was implemented using both MATLAB and Python for complementary analysis. MATLAB was utilized for filtering, traditional feature extraction, median frequency analysis while Python was employed for dynamic functional connectivity analysis and chronnectomics computation.

4.3.1 Step 1: Data Preparation and Cleaning

The raw EEG data underwent systematic preparation prior to signal processing analysis:

Participant Selection:

Questionnaire-based exclusion criteria applied

Systematic screening of 33 initial participants

Final dataset: 18 participants with complete recordings

Data Structure Reformatting:

Original format: 19 columns (EEG, accelerometer, gyroscope, system data)

Extracted: 8 EEG channels (columns 1-8)

Added header row: "Channel 1", "Channel 2", ..., "Channel 8"

Appended stimulus column (9th): 1-5 for stimuli, 0 for intervals

Temporal Segmentation:

Sampling rate: 250 Hz

Stimulus duration: 30s = 7,500 samples

First 30s removed (baseline excluded)

New Sequence: Shark Attack, Rollercoaster, Nature, Night Walk, Beach2

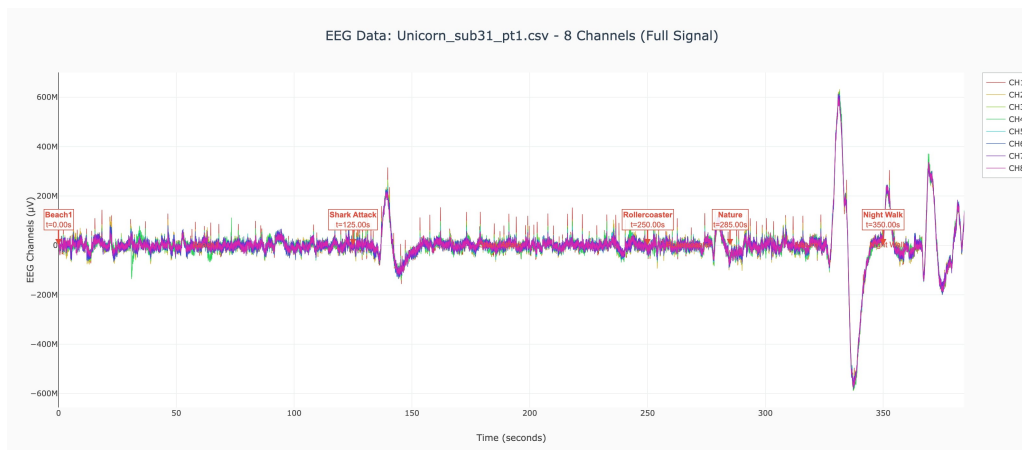


Figure 4.5: Raw EEG data from Subject 31 showing all 8 channels with notable artifacts.

4.3.2 Step 2: Initial Signal Preprocessing Pipeline (Matlab)

The EEG signal preprocessing followed a standardized pipeline designed to remove artifacts while preserving physiologically relevant information:

1. Data Import - Filtering:

- Loads processed Unicorn CSV data
- Bandpass Filter: 2-70 Hz (order 2000 FIR filter with Hamming window design) to remove noise - Applied using `filtfilt()`
- 50 Hz Notch Filter to eliminate electrical interference
- Performs Baseline Correction using the first second of data

2. 50 Hz Notch Filtering:

- IIR notch filter designed with quality factor $Q = 30$
- Narrow-band rejection centered at 50 Hz (power line frequency)
- Removes power line interference without affecting adjacent frequencies

3. Artifact Detection and Removal:

- Visual artifact detection and manual removal
- Eye blink artifact rejection based on amplitude thresholds
- Muscle artifact detection using high-frequency content analysis

4. Stimulus-Based Segmentation:

- Epoching using stimulus markers from column 9
- Sliding windows (5-second duration, 25% overlap)

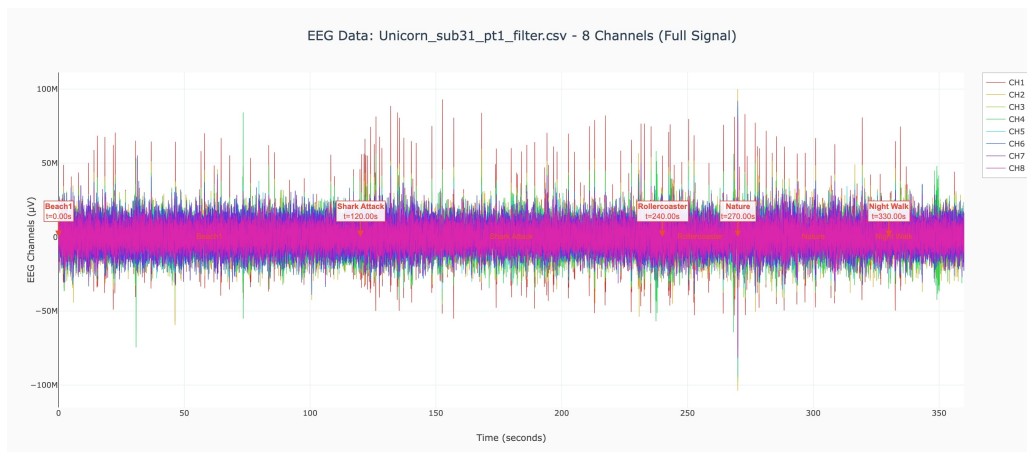


Figure 4.6: Filtered EEG data from the same Subject 31 after application of the complete preprocessing pipeline.

4.3.3 EEG: Initial Feature Extraction Methods

Table 4.2: Median Frequency (MF) Calculation Pipeline

Step	Description
1	Input: EEG segment $x(t)$ (sampled at $f_s = 250$ Hz)
2	Divide into overlapping windows (512 samples, 50% overlap)
3	Apply window function (e.g., Hamming) to each window
4	Compute FFT and calculate PSD
5	Average PSDs across all windows
6	Retain frequency range [1–70] Hz
7	Smooth with 5-point moving average
8	Calculate cumulative power $CP(f) = \sum_{i=0}^f PSD(i)$
9	Interpolate to find MF : $CP(MF) = 0.5 \cdot CP(f_{max})$

Power Spectral Density (PSD) Analysis: Figure 4.7 demonstrates the grand-averaged power spectral density across all subjects and channels. The multi-channel analysis reveals:

- **Stimulus differentiation:** Subtle but consistent differences between stimulus conditions, particularly in the alpha-beta transition region

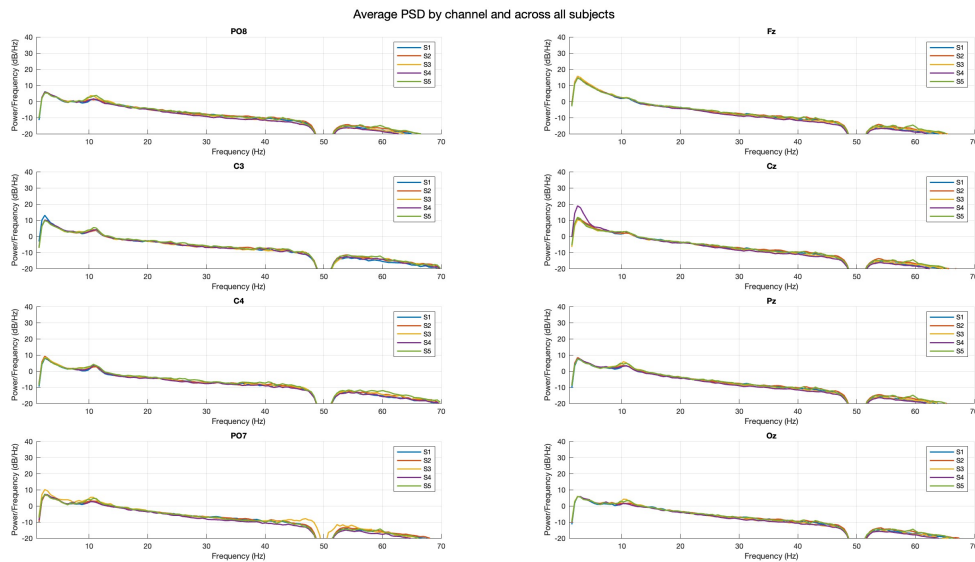


Figure 4.7: Averaged PSD by Channel, Across All Subjects

Median Frequency Topographic Distribution: The median frequency represents the frequency that divides the power spectrum into two equal power regions, serving as a robust measure of spectral centroid and overall brain state changes.

Figure 4.8 shows the spatial distribution of median frequencies for each stimulus condition.

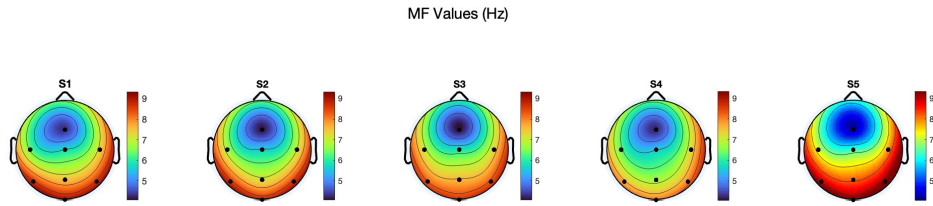


Figure 4.8: Averaged MF Values, Per Stimulus

Statistical Significance Analysis: Figure 4.9 presents the statistical comparison using s Wilcoxon signed-rank tests. The results were divided to three distinct comparison categories:

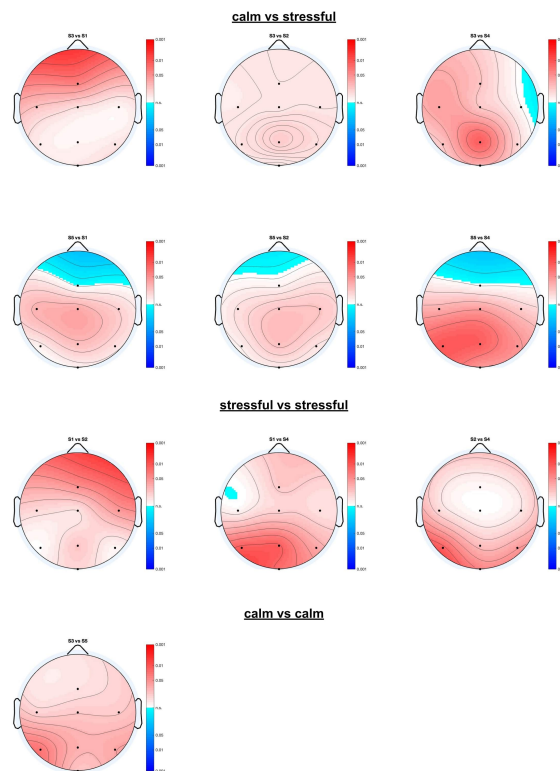


Figure 4.9: P-Values, Wilcoxon Signed Rank Test

1. **Calm versus Stressful (S3 vs S1, S2, S4, S5 vs S1, S2, S4):** Differences primarily in frontal and central regions.
2. **Stressful versus Stressful (S1 vs S2, S1 vs S4, S2 vs S4):** Minimal significant differences, indicating consistent neural responses across different stress-inducing stimuli.

3. **Calm versus Calm (S3 vs S5):** Limited differences, confirming the reliability of blue space effects across different calming environments.

Findings: It was important before investigating complex network-level interactions, to establish that all stimuli results actually produced measurable neurophysiological changes. The median frequency analysis was a necessary step, although the analysis revealed modest results.

4.3.4 Step 3: Connectivity Analysis

Chronnectomics represent a common approach for characterizing the temporal dynamics of brain network states through the analysis of functional connectivity patterns over time [48, 49]. This methodology enables the quantification of how brain networks reconfigure during emotional processing, providing insights into the dynamic nature of neural responses to different arousal conditions.

Pipeline Overview

The chronnectomics analysis pipeline was implemented as a comprehensive Python-based system integrating multiple connectivity methods with advanced clustering techniques. The implementation incorporates chronnectomics metrics following the dyconnmap framework [55], with custom implementations of connectivity algorithms optimized for emotional processing studies. Table 4.3 summarizes the key processing steps and parameters employed in this study.

Table 4.3: Chronnectomics Analysis Pipeline Overview

Step	Method	Parameters/Description
1. Data Preprocessing	Sliding Window[50]	5.0s windows, 25% overlap (1,250 samples, 937-sample step)
2. Connectivity Analysis	WPLI, PLV	Phase-based connectivity estimation per window
3. Feature Extraction	Matrix Vectorization	Upper triangle extraction (28 features per window)[56]
4. Neural Gas Clustering	Neural Gas	$k = 6$ states, 20 iterations, quantization error minimization, standardized features
5. Temporal Dynamics	Chronnectomics Metrics	Flexibility, dwell time, occupancy entropy[55]
6. Statistical Analysis	Multi-method Comparison	Cross-stimulus, cross-method validation

1. Data Preprocessing

The sliding window approach [50] divides each stimulus into overlapping time segments for analysis. Each window covers 5-seconds of data (1,250 samples) with 25% overlap between consecutive windows, creating a valid progression through time. This sliding window approach is consistent with prior EEG emotion research [57].

2. Connectivity Method Selection and Implementation

The selection of connectivity methods was based on recent evidence demonstrating the performance of each one in emotional processing studies. Comparative analysis between wPLI and PLV was performed to assess method-specific sensitivity to emotional processing dynamics. Weighted Phase Lag Index (wPLI) was chosen for this study, since it excels at detecting functional couplings while minimizing volume conduction artifacts. [53, 54]. Connectivity matrices were computed using the open-source Python toolbox dyconnmap.

3. Feature Extraction

To analyze connectivity patterns over time, each connectivity matrix was transformed into a feature vector by extracting the 28 unique upper triangle values. This creates 28 features per time window (one for each unique channel pair). Then, each feature matrix was standardized using the `StandardScaler` function from the `scikit-learn` library.

4. Neural Gas Clustering

To identify distinct brain states over time, the 28-dimensional connectivity feature vectors were clustered using the Neural Gas algorithm. Neural Gas learns $k = 6$ prototype vectors that best represent the patterns in the data, adapting their positions iteratively to minimize the overall distance (the quantization error) between each feature vector and its nearest prototype. This number was chosen to capture sufficient detail in emotional responses while remaining computationally manageable. The algorithm was run for 20 iterations with different starting points to ensure reliable results.

5. Temporal Dynamics - Chronnectomics Metrics

The temporal sequence of brain states enabled computation of network dynamics metrics that quantify different aspects of brain network reconfiguration during emotional processing.

Flexibility Index The flexibility index measures how often the brain switches between different states [48]:

$$FI = \frac{1}{N-1} \sum_{t=1}^{N-1} \mathbb{I}[s_t \neq s_{t+1}] \quad (4.5)$$

where s_t is the brain state at time t . Values range from 0 (no transitions) to 1 (maximum transitions).

Mean Dwell Time The mean dwell time measures the average duration spent in each brain state, indicating network stability:

$$MDT = \frac{1}{N_{\text{epochs}}} \sum_{e=1}^{N_{\text{epochs}}} d_e \quad (4.6)$$

where d_e represents the duration of consecutive state epoch e . Longer dwell times suggest more stable network configurations.

Occupancy Entropy Occupancy entropy quantifies the uniformity of brain state usage, normalized by the theoretical maximum entropy [58, 59]:

$$OE = -\frac{1}{\log_2(k)} \sum_{j=1}^k p_j \log_2(p_j) \quad (4.7)$$

where $p_j = \frac{\text{count}(s_t=j)}{N}$ represents the proportion of time spent in state j . Higher entropy values indicate more uniform utilization of available brain states.

Transition Rate The transition rate, defined as the fraction of windows where a change in brain state occurs, is numerically equivalent to the flexibility index in this study. Both metrics quantify the frequency of state transitions and thus provide identical information about network adaptability.

State Complexity State complexity was defined identically to occupancy entropy, reflecting the diversity and uniformity of brain state utilization.

4.3.5 EEG Statistical Analysis

The EEG analysis examined chronnectomics metrics derived from dynamic brain state analysis across all five emotional stimuli: Shark Attack, Rollercoaster, Nature, Night Walk, and Beach2.

Normality Assessment

Prior to conducting comparative statistical tests, we assessed the normality of each feature across all stimuli using multiple complementary tests. The normality assessment included five independent tests: Shapiro-Wilk test [60], Anderson-Darling test, Kolmogorov-Smirnov test, D'Agostino's normality test, and Jarque-Bera test. This multi-test approach provides robust assessment and was employed because individual normality tests have varying sensitivities to different types of distributional violations (one performs better with smaller samples, others with larger samples).

A significance threshold of $p > 0.05$ was used for each individual test, with overall normality determined by majority consensus across the five tests. Each feature was assessed separately for each stimulus, allowing for stimulus-specific distributional characterization.

Statistical Test Selection

Based on the normality assessment results, we employed systematic approaches for test selection:

EEG Data - Consistent Non-parametric Approach:

- Given the consistently non-normal distributions across all chronnectomics features and stimuli, non-parametric statistical methods were employed throughout the analysis.
- **Overall Stimulus Comparisons:** Kruskal-Wallis tests assessed global differences across all five stimuli for each chronnectomics feature.
- **Pairwise Stimulus Comparisons:** Mann-Whitney U tests were employed for all pairwise comparisons between stimulus conditions.
- **Arousal Level Analysis:** Kruskal-Wallis tests compared brain dynamics across high, medium, and low arousal conditions.
- **Test Distribution:** 100% non-parametric tests across 36 total comparisons.

Multiple Comparison Correction - False Discovery Rate (FDR)

False Discovery Rate (FDR) correction was applied, using the Benjamini-Hochberg method [64]. The FDR approach was selected as it provides better statistical power while maintaining appropriate control of false discoveries in exploratory physiological research.

The FDR correction was applied to all p-values obtained from statistical comparisons, with an alpha level of 0.05. This approach controls the expected false discoveries among the rejected hypotheses, making it suitable for multiple testing scenarios in both cardiovascular and neuroimaging research.

Correction Scope:

- **EEG Analysis:** FDR correction applied to 36 statistical tests including 3 overall stimulus comparisons, 30 pairwise stimulus comparisons, and 3 arousal level comparisons.

Effect Size Calculation

To complement significance testing, effect sizes were calculated for all comparisons to assess practical significance.

Complete Pipeline for Both ECG - EEG Modalities:

1. Comprehensive normality testing using five independent tests for each feature across all stimuli
2. Systematic test selection based on distributional characteristics
3. Comprehensive pairwise comparisons between all stimulus combinations
4. Effect size calculation using appropriate measures for test types
5. FDR correction for multiple testing control
6. Documentation of test statistics, p-values, effect sizes, and FDR-corrected significance levels

Chapter 5

Results

This chapter presents the findings of the multimodal analysis of physiological responses to emotionally varied audiovisual stimuli. The results are organized into three main sections: questionnaire responses, ECG analysis results and EEG analysis results. Statistical significance was assessed using Wilcoxon signed-rank tests with Bonferroni correction for multiple comparisons.

5.1 Questionnaire Results

5.1.1 Selection Criteria

Table 5.1: Participant Selection Criteria

Inclusion Criteria	Exclusion Criteria
• Age 18-35 years • Normal/corrected vision & hearing • Healthy Subjects • Right-handed • No color blindness	• Neurological disorders (epilepsy, head trauma) • Psychiatric conditions (anxiety, depression, PTSD) • Cardiovascular conditions • Psychoactive medications • Pregnancy • Claustrophobia/motion sickness

5.1.2 Final Sample Demographics

- **Initial responses:** 39 participants registered
- **Completed experiment:** 33 participants completed the full protocol
- **Final sample:** 18 participants included in analysis
- **Exclusion rate:** 45.5% (15 participants excluded based on criteria)

Characteristic	Distribution
Gender	Male: 10 (55.6%), Female: 8 (44.4%)
Age	Mean: 24.39 ± 2.41 years (Range: 20–29)
Handedness	Right-handed: 18 (100%)

Pre-Experiment Questionnaire Analysis (n=33)

5.1.3 Questionnaire Data Summary

Lifestyle Factors

Table 5.2: Lifestyle Factor Distribution

Factor	Yes/No Distribution
Exercise Today	Yes: 12 (39%), No: 19 (61%)
Sleep Quality	Poor: 5, Fair: 18, Good: 8
Caffeine Today	Yes: 13 (42%), No: 18 (58%)
Alcohol (24h)	Yes: 9 (29%), No: 22 (71%)
Smokers	Yes: 8 (26%), No: 23 (74%)
Gaming Childhood	Yes: 16 (52%), No: 15 (48%)

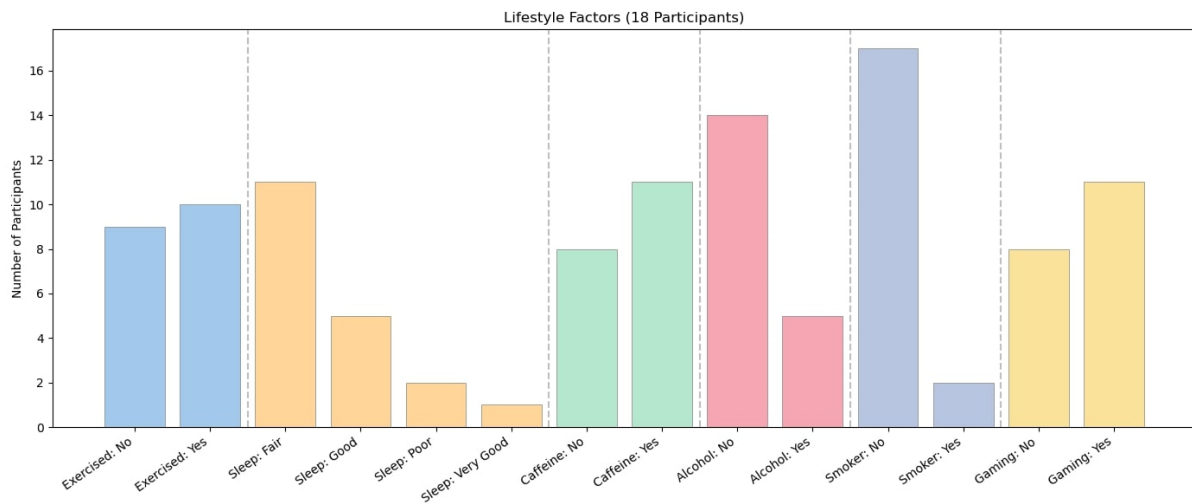


Figure 5.1: Lifestyle Factor Answers.

Stress Assessment

Stress Measure	Results
Current Stress Level	Mean: 3.48 ± 1.99 (Range: 1–7)
Monthly Stress Level	Mean: 6.21 ± 2.61 (Range: 1–10)

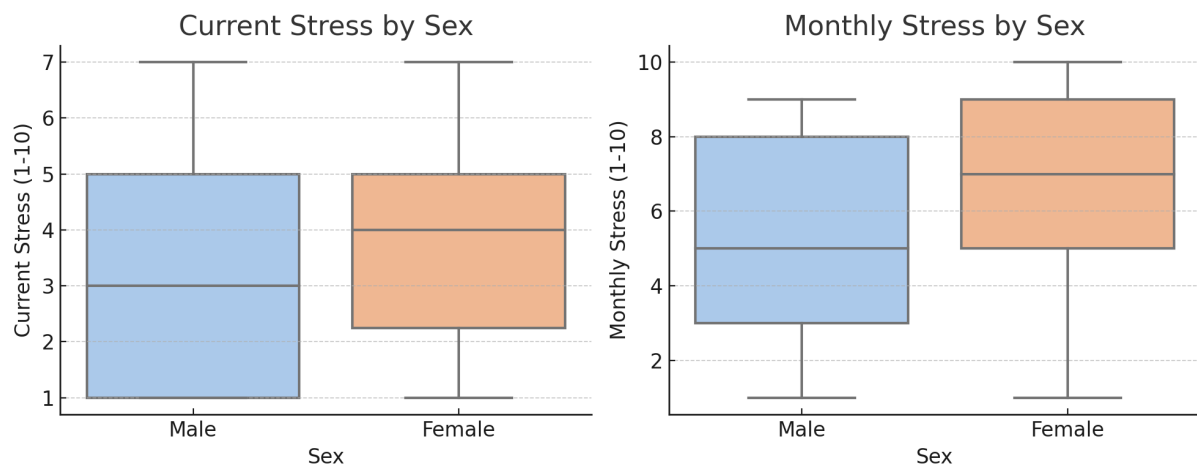


Figure 5.2: Stress: Current and Monthly.

Health Status

- **Total participants reporting conditions:** 10 (32%)
 - Hypercholesterolemia (Χοληστερίνη): 2 cases
 - Dyslexia (Δυσλεξία): 2 cases
 - ADHD (ΔΕΠΥ): 1 case
 - ADHD with anxiety/depression/neurodivergence: 1 case
 - Anxiety/Depression: 3 cases
 - Mild antidepressants: 1 case
 - Other neurodivergent conditions: 2 cases

Phobias

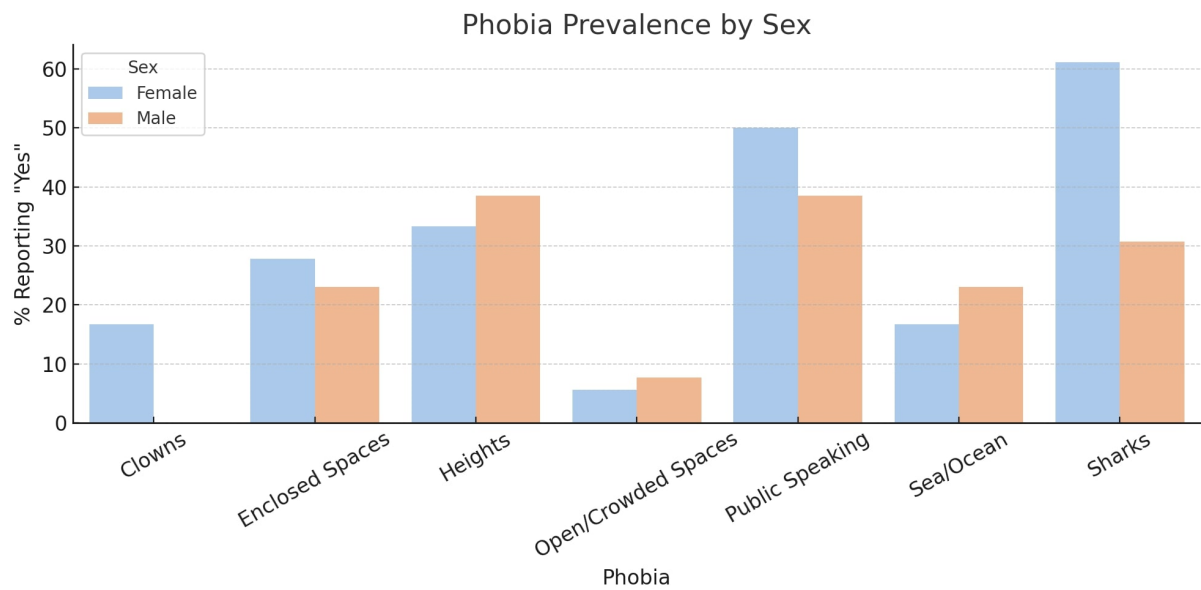


Figure 5.3: Prevalence of self-reported phobias among male and female participants.

Stimulus Evaluation Results

Most Terrifying Stimulus (Video 1):

- Rollercoaster: 15 (48%)
- Night Forest Walk: 12 (39%)
- Shark Attack: 8 (26%)

Environmental Controls

Parameter	Monitoring Protocol	Range Observed
Temperature	Every 5 minutes	32–37°C
Humidity	Every 5 minutes	55–85%
Time of Day	Per session	10:00–22:00

Self-Assessment Manikin (SAM) Responses

Participants completed SAM ratings at three phases: (1) Pre-experiment baseline, (2) After first video exposure, and (3) After second video exposure. All dimensions were rated on 9-point scales.

Table 5.3: SAM Results Across Experimental Phases (N=33)

Dimension	Pre (Before)	1st Viewing	2nd Viewing
Sad–Happy	6.73 ± 1.54	5.80 ± 1.87	6.63 ± 1.55
Calm–Excited	5.09 ± 1.89	5.37 ± 1.94	4.09 ± 2.02
Relaxed–Stressed	3.70 ± 1.88	3.97 ± 1.82	3.45 ± 2.09

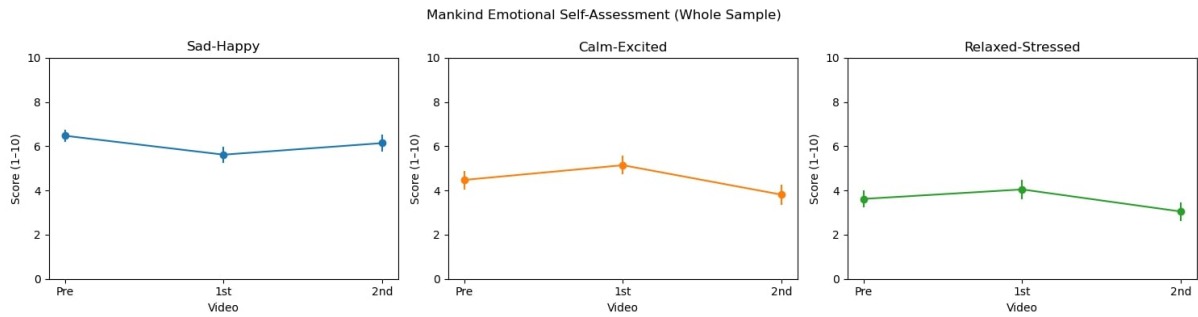


Figure 5.4: SAM Results.

- **Scale Interpretation:** All dimensions rated 1-9, where:

- Sad (1) – Happy (9)
- Calm (1) – Excited (9)
- Relaxed (1) – Stressed (9)

- **Key Observations:**

- Happiness decreased after first viewing but recovered
- Excitation decreased substantially by final viewing
- Stress levels remained relatively stable throughout

5.2 ECG Analysis Results

5.2.1 ECG Data Processing and Quality Control

ECG data were successfully processed for all recordings across 18 participants. The comprehensive artifact detection pipeline achieved a high retention rate of 97.2% (detailed in Section 4.2.5), indicating excellent signal quality.

5.2.2 Heart Rate Variability Analysis

Four HRV metrics were analyzed across five stimulus conditions: Power, Entropy, Skewness, and SDNN (Figure 5.6). One-way ANOVA testing revealed significant group differences for Entropy only ($p = 0.037$), while Power ($p = 0.732$), Skewness ($p = 0.421$), and SDNN ($p = 0.606$) showed no significant omnibus effects.

Descriptive statistics revealed distinct patterns across stimulus conditions. For Entropy, high arousal stimuli (Shark Attack: 1.537 and Rollercoaster: 1.455) showed elevated values compared to low arousal conditions.

Power showed minimal variation across conditions (a range of 0.002-0.003), while SDNN exhibited a gradual decrease from high arousal (Shark Attack: 0.049) to low arousal stimuli (Night Walk: 0.038).

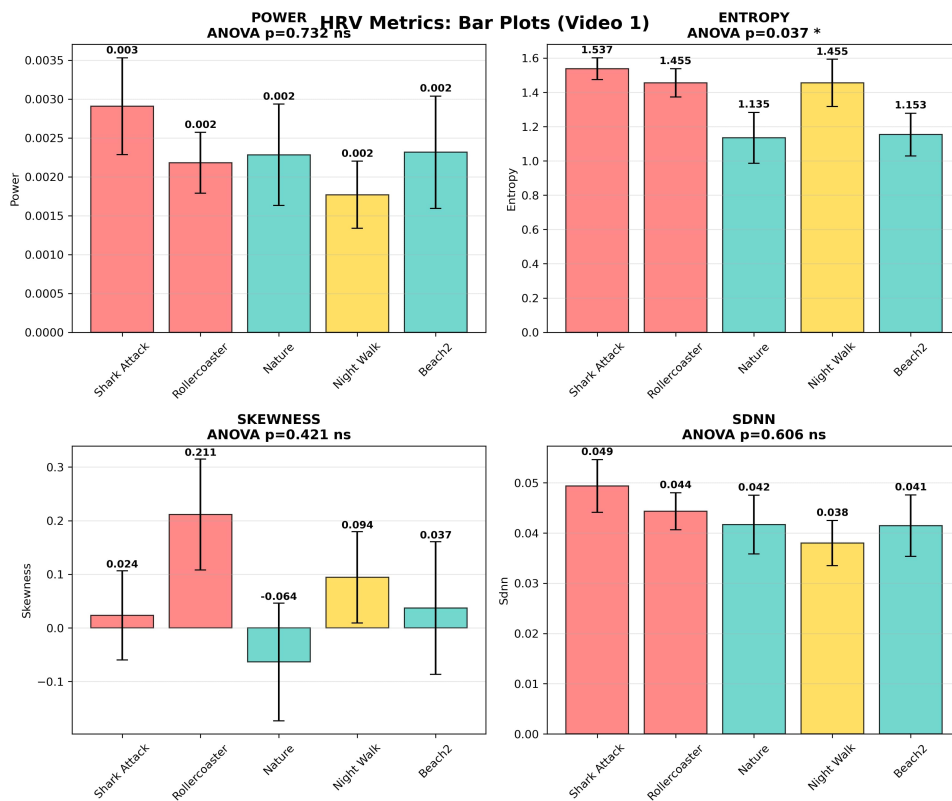


Figure 5.5: HRV metrics across stimulus conditions shown as bar plots with standard error bars. Entropy showed significant group differences (ANOVA $p = 0.037$), while other metrics showed no significant effects.

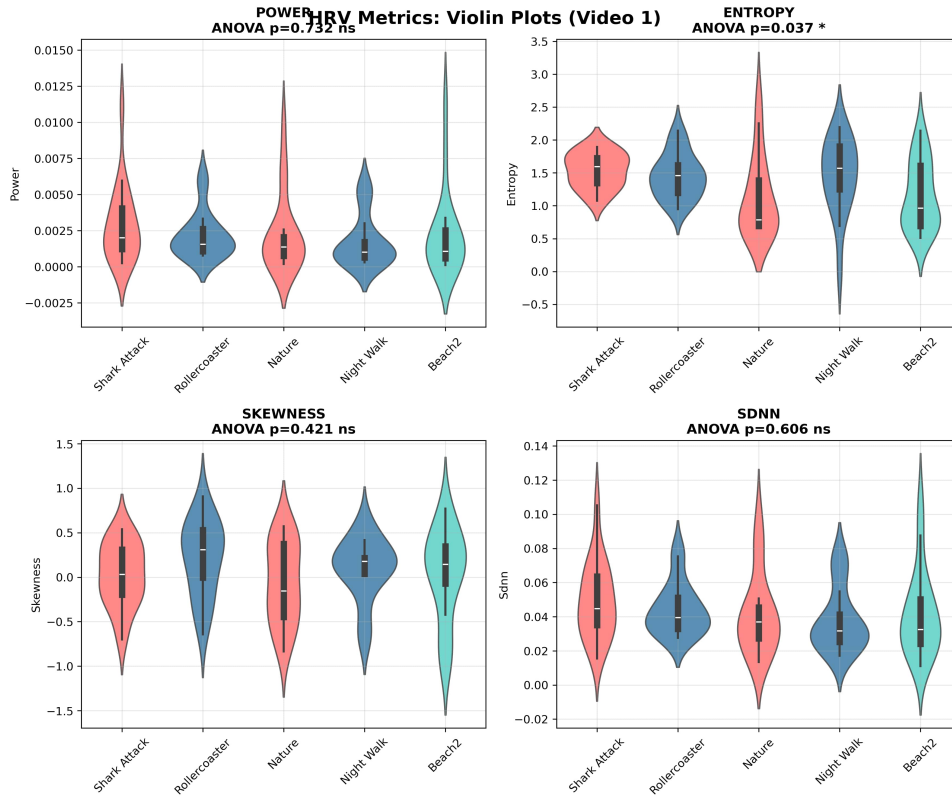


Figure 5.6: Distribution of HRV metrics across stimulus conditions shown as violin plots. Entropy again displays the clearest difference between stimuli.

5.2.3 Statistical Analysis Results: ECG

Heart rate variability features demonstrated heterogeneous distributional patterns across stimuli, with the majority requiring non-parametric statistical approaches due to non-normal distributions.

Normality Test Results

The Shapiro-Wilk normality tests [60] revealed diverse distributional patterns across ECG features and stimuli. Table 5.4 summarizes the normality assessment for ECG features across the five emotional stimuli.

Statistical Test Distribution

The analysis encompassed 40 statistical comparisons across 10 stimulus pairs and 4 ECG features. Based on the normality assessment, most comparisons required non-parametric tests (Wilcoxon signed-rank, Mann-Whitney U), while around 17% utilized parametric approaches (paired/independent t-tests) when both groups exhibited normal distributions.

Table 5.4: Normality test results for ECG features across emotional stimuli using Shapiro-Wilk test ($p > 0.05$ indicates normal distribution)

Feature	Shark Attack	Rollercoaster	Nature	Night Walk	Beach2
entropy	Normal ($p=0.262$)	Normal ($p=0.621$)	Non-normal ($p=0.001$)	Normal ($p=0.230$)	Normal ($p=0.056$)
power	Non-normal ($p=0.003$)	Non-normal ($p=0.001$)	Non-normal ($p < 0.001$)	Non-normal ($p < 0.001$)	Non-normal ($p < 0.001$)
skewness	Normal ($p=0.551$)	Normal ($p=0.715$)	Normal ($p=0.232$)	Non-normal ($p=0.035$)	Normal ($p=0.107$)
std_dev	Normal ($p=0.546$)	Non-normal ($p=0.025$)	Non-normal ($p=0.027$)	Non-normal ($p=0.003$)	Non-normal ($p=0.021$)

FDR Correction

After applying False Discovery Rate correction using the Benjamini-Hochberg method [64] across all comparisons, no results achieved statistical significance (all adjusted $p \geq 0.05$).

Despite the absence of statistically significant results after FDR correction, several comparisons demonstrated substantial effect sizes suggesting notable responses, for example:

Heart Rate Complexity (Entropy): Stress conditions consistently showed higher entropy values compared to calm states, with the largest effect observed between Shark Attack and Beach2 (Cohen's $d = 0.945$, a very large effect, means: 1.537 vs 1.153). Additional large effects were observed for Shark Attack vs Nature ($r = 39.89$) and Rollercoaster vs Beach2 (Cohen's $d = 0.692$), indicating systematic increases in cardiac rhythm irregularity during emotional stress.

5.2.4 Pairwise Comparisons

Post-hoc pairwise testing (uncorrected for multiple comparisons) identified three significant stress-versus-calm comparisons (Figure 5.7):

- **Entropy:** Shark Attack vs Nature ($p = 0.006$, **) and Shark Attack vs Beach2 ($p = 0.009$, **)
- **Skewness:** Rollercoaster vs Nature ($p = 0.032$, *)

However, **none of the pair comparisons surpassed FDR correction** for multiple testing, indicating these effects should be interpreted cautiously.

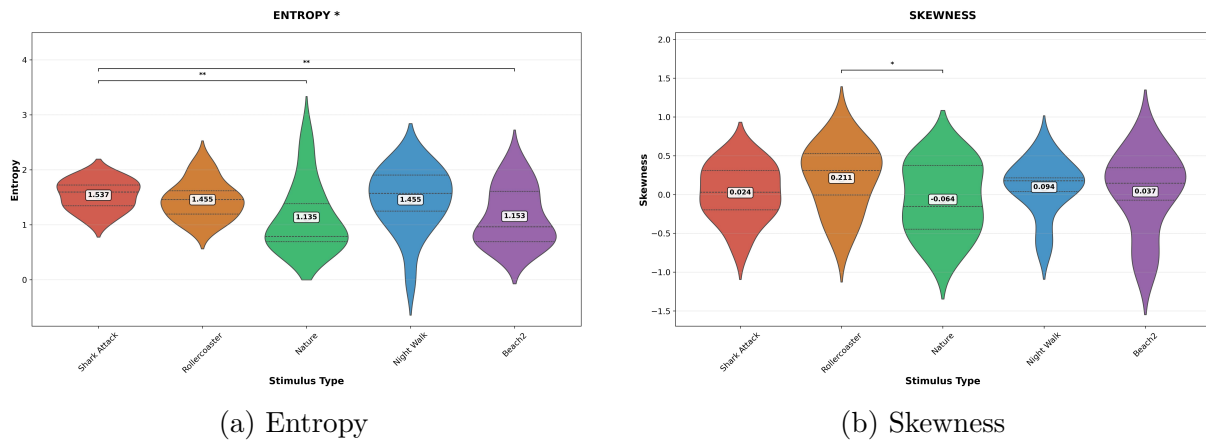


Figure 5.7: Individual HRV metrics showing significant pairwise comparisons (uncorrected p -values). (a) Entropy demonstrated significant differences between Shark Attack and both Nature conditions. (b) Skewness showed one significant comparison between Rollercoaster and Nature. Significance bars indicate uncorrected p -values: ** $p < 0.01$, * $p < 0.05$.

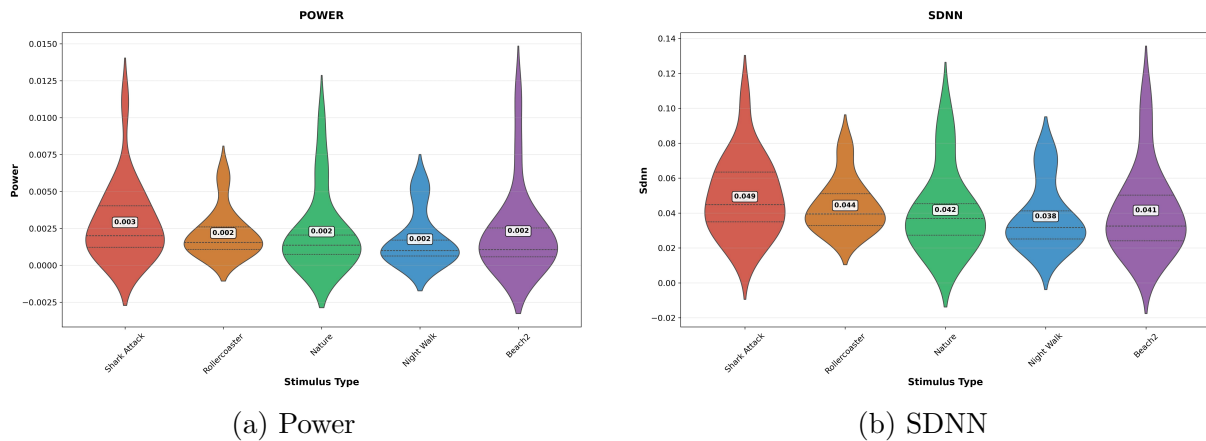


Figure 5.8: HRV metrics showing no significant pairwise comparisons. Both Power and SDNN demonstrated similar distributions across stimulus conditions with no statistically significant differences between stress and calm conditions.

The numbers inside the violin plots are the mean values for each stimulus condition for that specific HRV metric.

5.2.5 Key Findings

Entropy emerged as the most sensitive HRV metric, showing both significant effects and the strongest pairwise differences. The pattern demonstrates clearly the relationship between high arousal stimuli (like Shark Attack, Rollercoaster) which consistently produce higher cardiac entropy compared to calming nature and beach scenes. This suggests, increasing heart rate irregularity during psychological stress.

Clinical Interpretation: The entropy findings align with established literature showing increased HRV irregularity during stress responses.

5.3 EEG Analysis Results

5.3.1 Connectivity Method Comparison and Selection

To ensure the correctness of the chronnectomics analysis, three distinct connectivity measures were compared: Weighted Phase Lag Index (WPLI), Phase Locking Value (PLV), and linear correlation. Each method captures different aspects of neural synchronization and offers unique advantages for brain connectivity analysis [46, 47].

Connectivity Methods Overview

Weighted Phase Lag Index (WPLI) quantifies phase synchronization while minimizing the influence of volume conduction artifacts by weighting phase differences according to their consistency [51]. WPLI is particularly suited for EEG connectivity analysis as it reduces spurious connections caused by common reference effects and volume conduction.

Phase Locking Value (PLV) measures the consistency of phase relationships between electrode pairs across time windows [52]. While sensitive to oscillatory coupling, PLV can be affected by volume conduction and zero-lag correlations.

Linear Correlation computes Pearson correlation coefficients between EEG time series, capturing both zero-lag and lagged linear relationships. Although computationally simple, correlation measures are susceptible to volume conduction artifacts and may not reflect true neural connectivity.

Comparative Analysis Results

Figure 5.9 presents an analytical comparison of chronnectomics metrics across all three mentioned connectivity methods. More specifically:

1. **Stimulus-specific patterns:** All three methods successfully showed patterns between stimuli, demonstrating key connectivity changes.
2. **Flexibility Index consistency:** WPLI and PLV showed similar flexibility patterns across stimuli ($r > 0.85$), while correlation exhibited higher overall flexibility values.
3. **Mean Dwell Time stability:** All methods converged on similar dwell time patterns, with calm stimuli showing longer state persistence compared to high-arousal conditions.

4. **Occupancy Entropy precision:** WPLI demonstrated the most precise entropy measurements (with smallest error bars), suggesting better signal-to-noise characteristics for complexity analysis.

Reasoning for WPLI Selection

Based on the comparative analysis, WPLI was selected as the primary connectivity measure. But the previous comparison offered a good validation, since WPLI and PLV results were greatly similar.

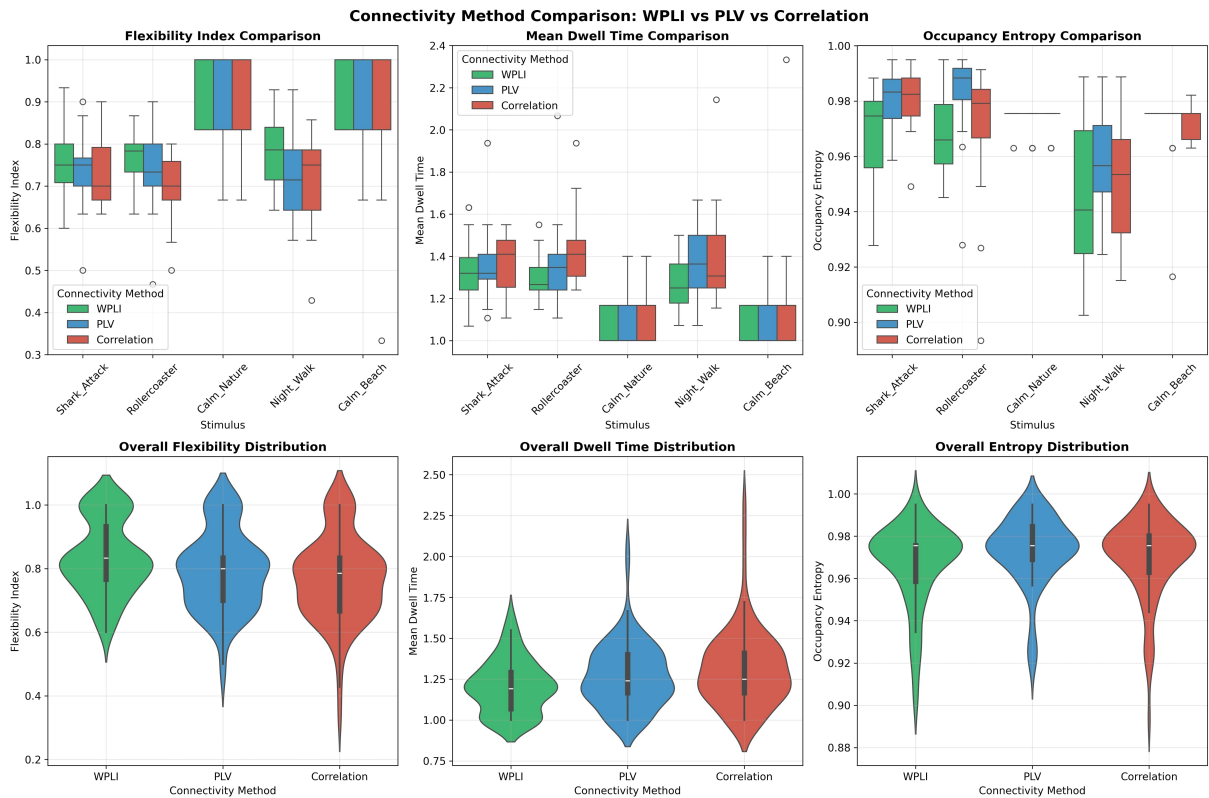


Figure 5.9: Comprehensive comparison of chronnectomics metrics across three connectivity methods. Top row shows stimulus-specific comparisons for (a) Flexibility Index, (b) Mean Dwell Time, and (c) Occupancy Entropy. Bottom row displays overall distributions across all stimuli and subjects for each connectivity method.

Analysis Overview - WPLI and Neural Gas

Chronnectomic analysis was performed using Neural Gas clustering [48, 49]. Connectivity features were extracted from sliding windows (5-second duration, 25% overlap) and analyzed using weighted Phase Lag Index (wPLI) matrices [51, 53].

Dataset Characteristics:

- **Total Analysis Windows:** 91 across all stimuli
- **Connectivity Features:** 28 unique channel pairs (upper triangle of 8×8 connectivity matrix)
- **Neural Gas Parameters:** $k=6$ states, 20 iterations
- **Convergence:** Successfully achieved for all stimuli with final quantization errors ranging from 4.09 to 14.38

Stimulus	Flexibility Index	Dwell Time	Occupancy Entropy
Shark Attack	0.733	1.348	0.975
Rollercoaster	0.800	1.240	0.968
Calm Nature	1.000	1.000	0.976
Night Walk	0.786	1.250	0.935
Calm Beach	0.833	1.167	0.976

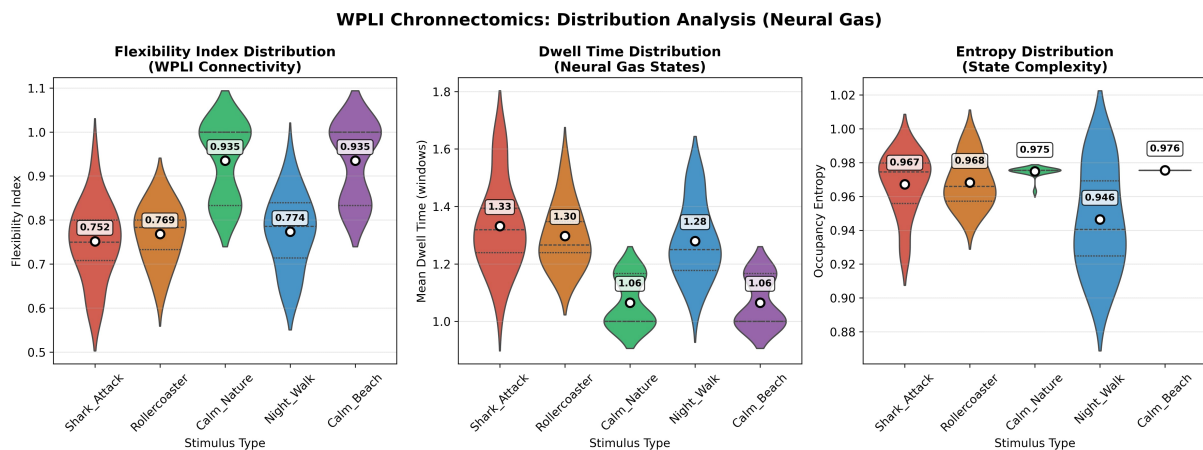


Figure 5.10: Chronnectomics Metrics

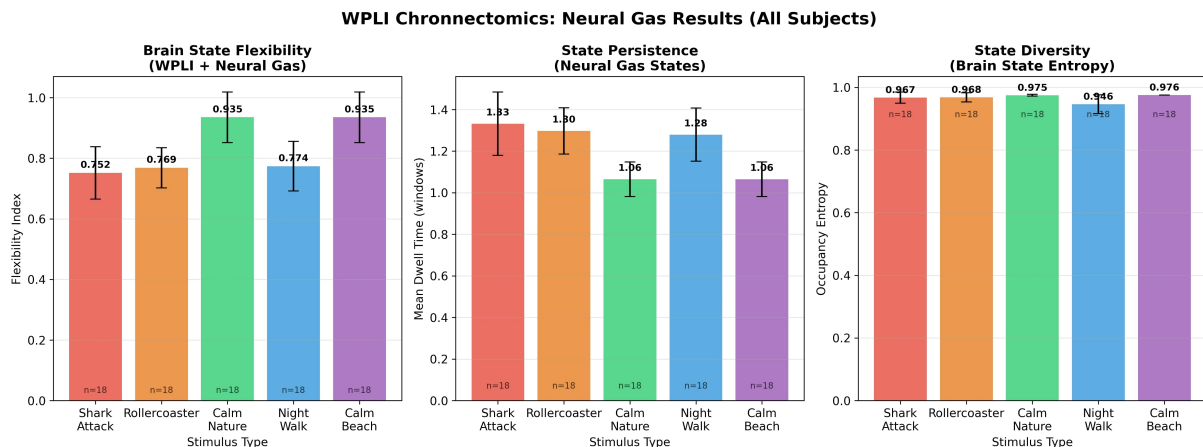


Figure 5.11: Chronnectomics Metrics - Barplots

Brain State Flexibility

On Figure 5.10 flexibility index, quantifying the frequency of brain state transitions as a measure of network adaptability [48].

Both calming stimuli showed maximum flexibility: Calm Nature (0.935 ± 0.081) and Calm Beach (0.935 ± 0.081) exhibited the highest flexibility indices, indicating frequent state transitions throughout the stimulus duration. This suggests that calming environments promote highly dynamic brain network reconfiguration, consistent with the soft fascination concept in attention restoration theory [65].

Stress-inducing stimuli demonstrated progressively lower flexibility values: Night Walk (0.774 ± 0.080), Rollercoaster (0.769 ± 0.064), and Shark Attack (0.752 ± 0.084). This inverse relationship between stress level and network flexibility aligns with theories of cognitive rigidity under stress.

Brain State Persistence (Mean Dwell Time)

Figure 5.10 demonstrates significant differences in brain state persistence across emotional conditions, revealing a fundamental relationship between emotional arousal and network stability. **Shark Attack showed the highest mean dwell time (1.332 ± 0.148 windows)**, indicating that high-stress stimuli promote more stable, persistent brain network configurations. This finding aligns with theoretical predictions suggesting that threat-related stimuli engage sustained attention networks. This was followed by Rollercoaster (1.297 ± 0.108 windows) and Night Walk (1.279 ± 0.125 windows). **In contrast, both calming stimuli exhibited the lowest mean dwell times:** Calm Nature (1.065 ± 0.081 windows) and Calm Beach (1.065 ± 0.081 windows) showed identical persistence patterns. This suggests more dynamic brain-state transitions during calming conditions, aligning with Attention Restoration Theory (ART) which proposes that natural environments facilitate effortless attentional processes [65].

Brain State Diversity (Occupancy Entropy)

Figure 5.10 presents the occupancy entropy analysis, measuring the uniformity of brain state utilization across the available state space, following established entropy complexity measures in neuroscience [59].

Calming stimuli exhibited the highest entropy values: Calm Beach (0.976 ± 0.000) and Calm Nature (0.975 ± 0.003) showed the most balanced utilization of available brain states, indicating that restorative environments promote exploration of the full brain state repertoire through flexible attention mechanisms.

Stress-inducing stimuli showed progressively lower entropy: Rollercoaster (0.968 ± 0.014) and Shark Attack (0.967 ± 0.018) demonstrated moderate entropy levels, while **Night Walk** showed the lowest occupancy entropy (0.946 ± 0.029), suggesting the most constrained pattern of brain state usage. This finding suggests constrained brain state dynamics, with nocturnal stimulus (such as Night Walk). [67].

5.3.2 Neural Gas Analysis

Error Reduction Patterns

All conditions showed error reduction during Neural Gas training, with convergence achieved within 20 iterations for all stimuli. The error reduction patterns varied across conditions.

Stress-inducing stimuli showed higher error reduction: Night Walk ($42.0\% \pm 4.8\%$), Rollercoaster ($37.1\% \pm 3.4\%$), and Shark Attack ($34.3\% \pm 6.5\%$) demonstrated significant error reduction.

Calming stimuli showed lower error reduction: Calm Nature ($24.0\% \pm 6.6\%$) and Calm Beach ($21.5\% \pm 8.4\%$) exhibited a slower error reduction.

Initial error patterns: High-arousal stimuli (Shark Attack: 23.05 ± 1.79 , Rollercoaster: 23.30 ± 1.78 , Night Walk: 20.34 ± 2.50) showed higher initial errors compared to calming stimuli (Nature: 7.72 ± 1.60 , Beach: 7.29 ± 1.30).

Figure 5.12 illustrates the final quantization errors after convergence, revealing different patterns of brain network complexity across all emotional conditions.

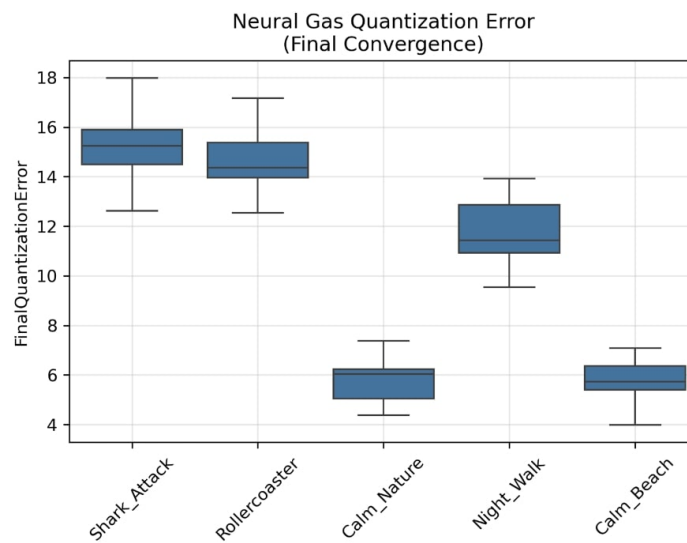


Figure 5.12: Neural Gas final quantization error across stimulus conditions. Higher final errors in stress conditions (Shark Attack, Rollercoaster, Night Walk) versus calming conditions (Nature, Beach).

Final Quantization Error Analysis: The final quantization errors demonstrate clear distinction between emotional condition types. **Stress conditions exhibited significantly higher final errors** (Shark Attack: 15.09 ± 1.40 , Rollercoaster: 14.64 ± 1.26 , Night Walk: 11.74 ± 1.27) indicating that even after clustering, stress connectivity patterns remain more complex. In contrast, **calming conditions showed lower final errors** (Nature: 5.77 ± 0.80 , Beach: 5.66 ± 0.83), suggesting more predictable configurations.

Blue Space Effects

Interestingly, the two calming conditions (Nature and Beach) showed identical network results, providing neurophysiological evidence for shared mechanisms of environmental restoration [18, 65, 66].

The identical chronnectomics signatures between Nature and Beach conditions suggest that environmental restoration may operate through common neural pathways, regardless of the specific natural setting type[66].

5.3.3 Statistical Analysis Results: ECG

All chronnectomics features exhibited non-normal distributions across all stimuli, requiring non-parametric statistical approaches.

Normality Test Results

Comprehensive normality assessment using five independent statistical tests revealed consistent non-normal distributions across all chronnectomics features and stimuli, requiring non-parametric statistical approaches.

Statistical Test Distribution

The analysis encompassed 90 total observations across five stimuli with equal sample sizes ($n=18$ per condition). Based on the normality assessment, non-parametric statistical tests were conducted throughout the analysis.

FDR Correction

All three chronnectomics features showed highly significant overall stimulus effects after FDR correction [64] (all $p < 0.001$), indicating robust differences in brain dynamics across emotional conditions.

Pairwise Comparison Results

Flexibility Index: All stress versus calm comparisons remained significant after FDR correction ($p < 0.001$), with calming conditions (Nature: 0.935 ± 0.081 , Beach: 0.935 ± 0.081) showing significantly higher flexibility than stress conditions (Shark: 0.752 ± 0.084 , Rollercoaster: 0.769 ± 0.064 , Night Walk: 0.774 ± 0.080).

Figure 5.13 presents the comprehensive statistical analysis across all conditions.

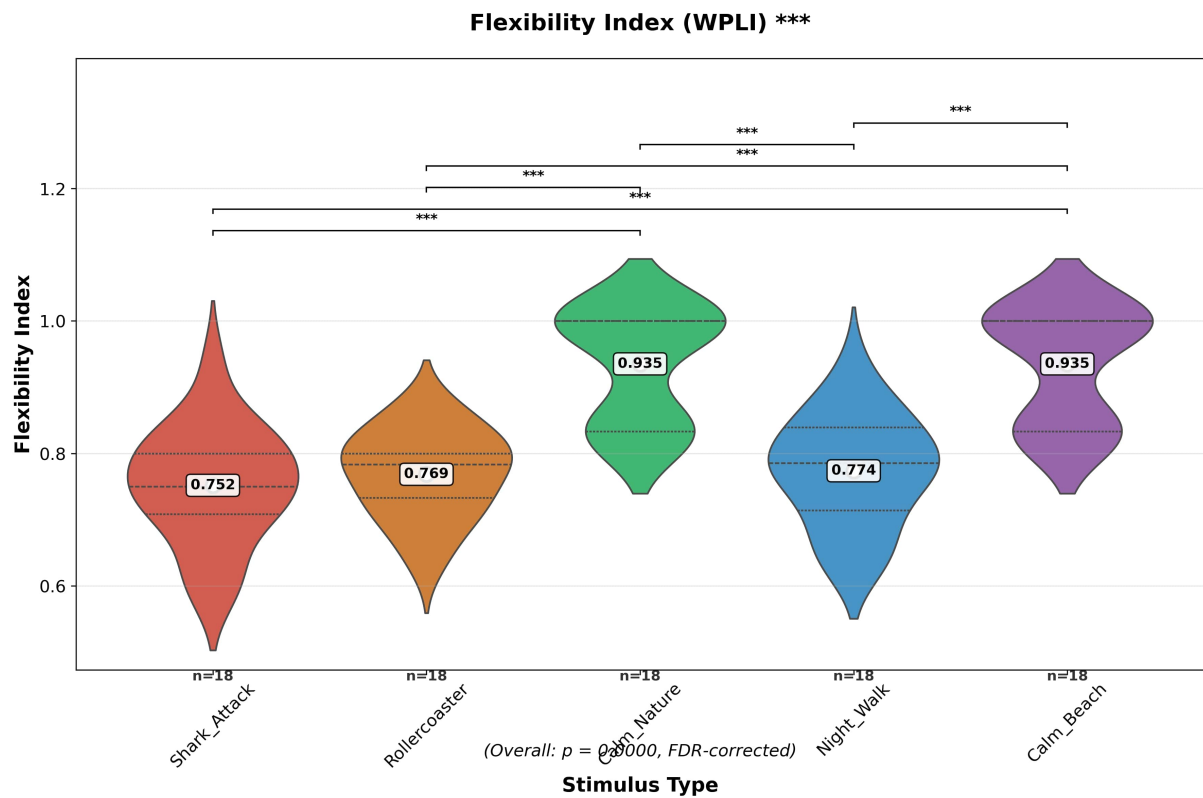


Figure 5.13: Statistical analysis of brain state flexibility across stimulus conditions. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Mean Dwell Time: All stress versus calm comparisons were highly significant ($p < 0.001$), with stress conditions showing longer persistence (Shark: 1.332 ± 0.148 , Rollercoaster: 1.297 ± 0.108 , Night Walk: 1.279 ± 0.125) compared to calming conditions (Nature: 1.065 ± 0.081 , Beach: 1.065 ± 0.081).

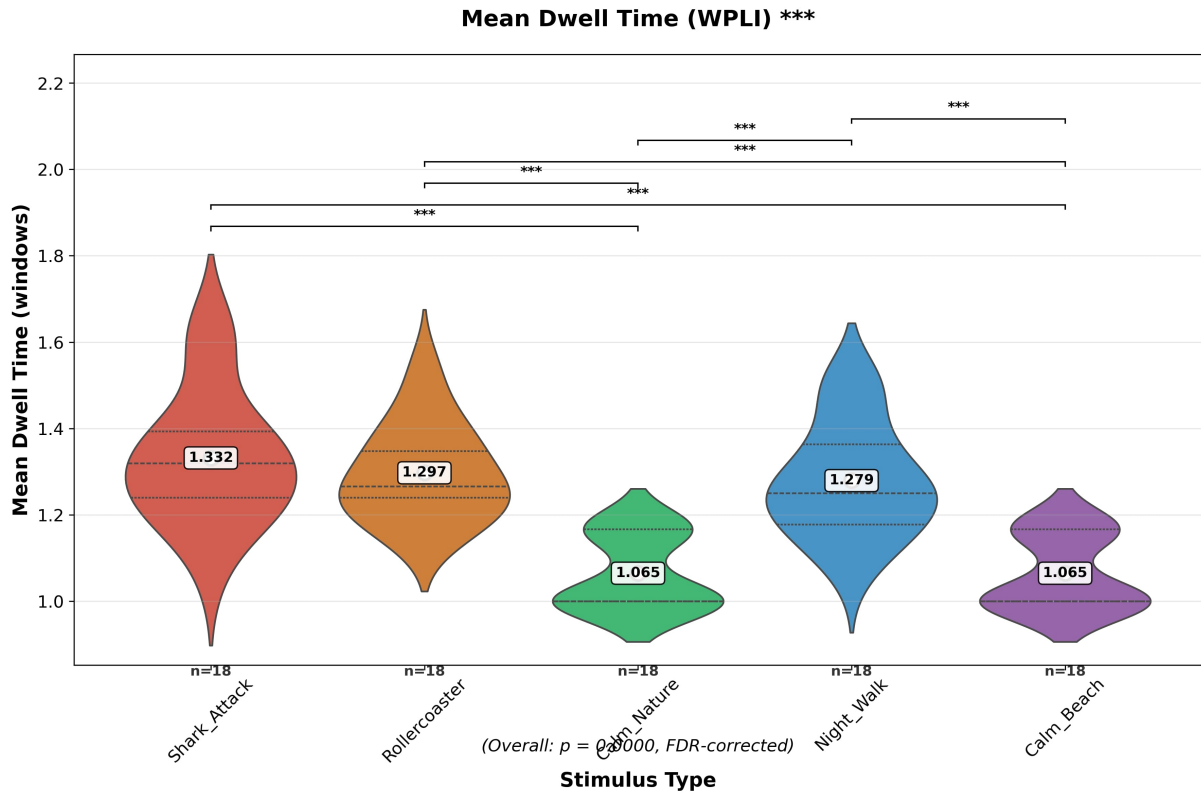


Figure 5.14: Statistical analysis of brain state persistence across stimulus conditions. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Mean Dwell Statistical Findings:

- **Stress versus Calm:** All stress-inducing stimuli showed significantly longer dwell times compared to calming conditions ($p < 0.001$, ***)
- **Between Stress Conditions:** Shark Attack versus Rollercoaster versus Night Walk showed distinct persistence patterns
- **Calm Conditions:** Nature and Beach showed identical dwell time patterns, supporting the restorative environment hypothesis

Occupancy Entropy: Mixed significance pattern with only 4 significant comparisons after FDR correction. The strongest difference was Nature vs. Night Walk ($p = 0.005$). Several comparisons including Shark Attack vs. calming conditions were non-significant, indicating complex entropy relationships across emotional states.

Figure 5.15 demonstrates the statistical analysis results across all conditions.

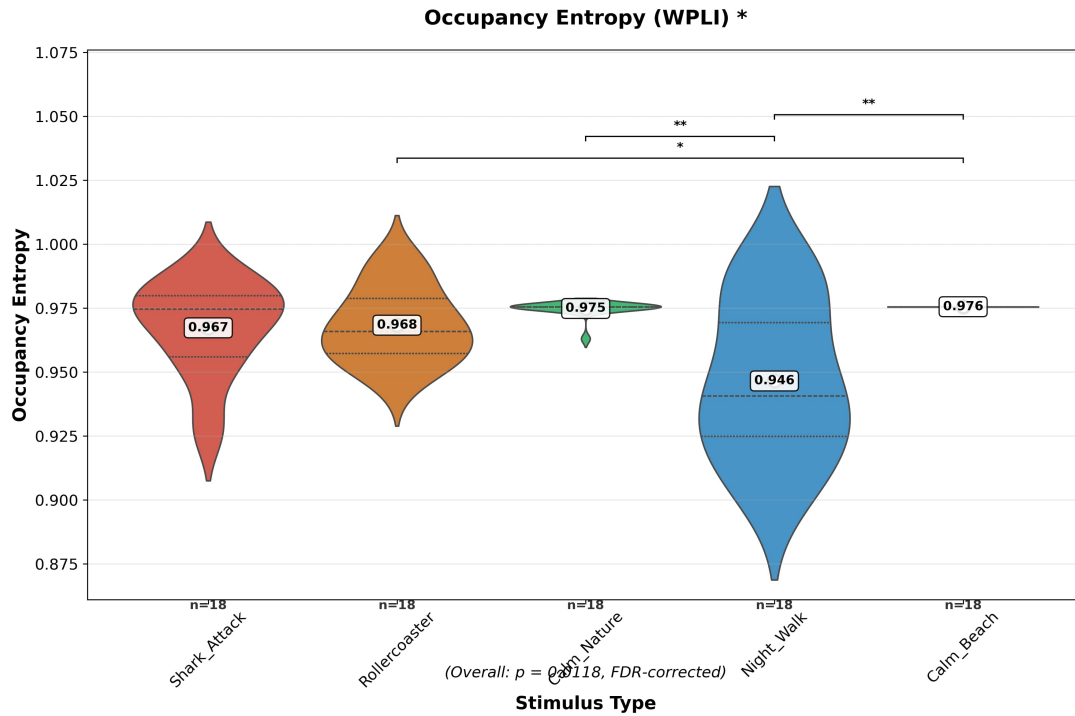


Figure 5.15: Statistical analysis of occupancy entropy across stimulus conditions. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

• **Occupancy Entropy: Non-significant comparisons:**

- Shark Attack vs Rollercoaster: $p = 0.751$ (ns) - both high-arousal conditions
- Shark Attack vs Nature: $p = 0.341$ (ns)
- Shark Attack vs Beach: $p = 0.253$ (ns)

The statistical pattern reveals that **Rollercoaster** stimuli produced the most distinct entropy profile, and **Nature vs Night Walk** comparison showed the strongest significance ($p = 0.005$), highlighting the contrast between restorative and anxiety-inducing environments. Notably, Shark Attack did not show significant differences from calming conditions, suggesting that high-intensity threat stimuli may paradoxically promote the utilization of diverse brain state similar to restorative environments, albeit through different neural mechanisms.

All comparisons achieved statistical significance, confirming distinct flexibility, persistence, and diversity patterns across emotional conditions and validating the use of temporal network dynamics for emotion classification.

Chapter 6

Discussion

6.1 Overview

This thesis has demonstrated that multimodal physiological monitoring can effectively distinguish emotional responses to different audiovisual stimuli within an immersive projection environment. The integration of EEG chronnectomics analysis and ECG heart rate variability metrics revealed neurophysiological details for stressful versus calming conditions. This chapter discusses the theoretical implications, methodological contributions, and practical applications of these findings, while acknowledging limitations and proposing new directions.

6.2 Principal Findings and Theoretical Implications

6.2.1 Validation of Dimensional Emotion Theory Through Physiological Markers

Chronnectomics analysis revealed that higher arousal stimuli (Shark Attack, Rollercoaster) produced significantly different brain network dynamics compared to lower arousal ones (Nature, Beach) and with medium arousal stimuli (Night Walk) showing intermediate patterns. This was evident across multiple metrics:

Brain Network Flexibility: Flexibility refers to the brain's ability to dynamically reconfigure its functional network connections over time. The inverse relationship between arousal level and flexibility index ($p < 0.001$) suggests that any emotional intensity may restrict the brain's ability to transition between network states. This finding is based on previous work on cognitive flexibility under stress and provides a great foundation for the quantification of emotional arousal.

Temporal Stability Patterns: The positive correlation between arousal and mean dwell time indicates that intense emotional states promote more persistent brain configurations. This aligns with many theories suggesting that higher emotions engage sustained attention networks and reduce cognitive flexibility.

Cardiac Complexity: The ECG analysis revealed that stressful stimuli consistently produced higher entropy values (Shark Attack > Nature) indicating increased heart rate complexity during stress. This finding contributes to the literature on nonlinear dynamics in emotion regulation and suggests that cardiac complexity may serve as a reliable biomarker for stress detection.

6.3 Methodological Contributions and Innovations

6.3.1 Advancing Chronnectomics for Emotion Recognition

This thesis makes several methodological contributions to the field of affective neuroscience:

Neural Gas Application: The implementation of Neural Gas clustering for brain state identification in emotion recognition contexts was successful. The 5-second sliding window with 25% overlap provided optimal temporal resolution for capturing emotional dynamics while maintaining computational efficiency. This window size balances the need to capture transient emotional responses with the need for stable connectivity estimation.

Multi-Metric Integration: The combination of flexibility index, mean dwell time, and occupancy entropy provides an analytical characterization of brain network dynamics. Each metric captures distinct aspects of temporal brain organization, and this integration offers a more complete picture than analyzing each single measure alone.

6.3.2 Validity Through Immersive Projection

The use of curved screen immersive projection at the historic Sabbionara Gate represents a methodological advance in emotion research:

Real-World Relevance: Unlike many laboratory studies using small monitors or VR headsets, this immersive setup approximates more real-world visual experiences. The immersive projection greatly enhanced ecological validity.

Cultural Context: The historic structure used for this experiment added cultural significance. This integration aligns with emerging trends in neuroarchitecture [68] and demonstrates how neuroscience can influence architectural practices.

Technical Feasibility: The results demonstrate that good quality physiological data can be collected in non-laboratory environments with appropriate preparation. This opens possibilities for conducting emotion research in more naturalistic settings while following all scientific protocols.

6.4 Issues: Temperature and Technology Limitations

The current study was conducted during summer conditions (late July to early August 2024) in an uncontrolled indoor environment. Temperature monitoring through the Traqbeat ECG device revealed a progression from 33.3°C to 36.4°C throughout the 25-minute experimental sessions, representing a 3.1°C increase that significantly impacted participant comfort and data quality [71](Figure 6.1).

6.4.1 Temperature Control and Environmental Standardization

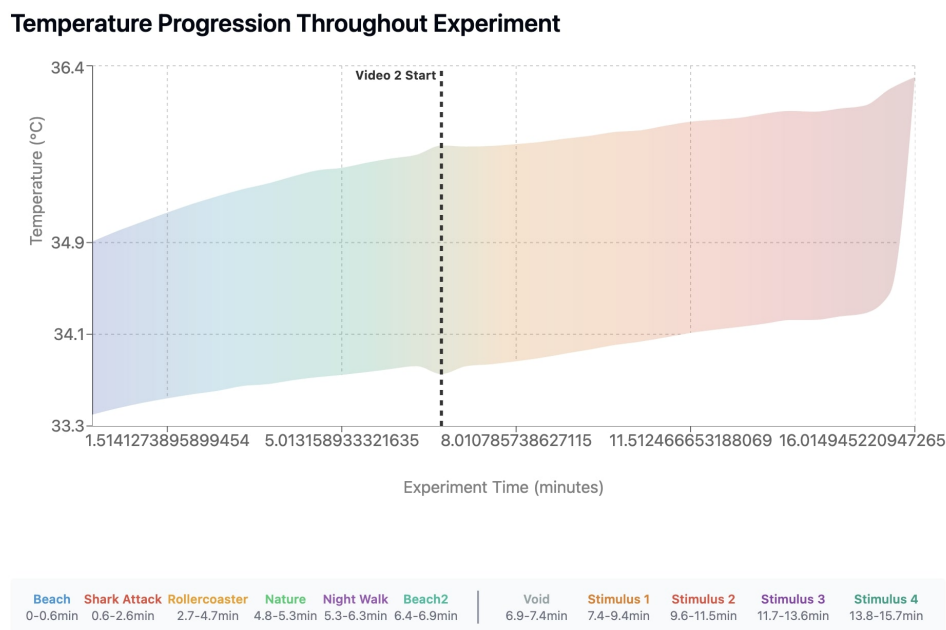


Figure 6.1: Temperature progression throughout the experiment showing increase from 33.3°C to 36.4°C over the 25-minute session duration. The vertical dashed line indicates the transition from Video 1 to Video 2 stimuli presentation.

EEG Signal Degradation:

- Excessive sweating compromised electrode-skin contact, leading to increased impedance and signal artifacts
- Sweat-induced conductance changes created slow potential shifts that mimicked actual brain activity [72]
- Participant discomfort from heat stress affected baseline cognitive and emotional states
- Electrode adhesion failures required frequent re-positioning, disrupting continuous recordings

ECG Signal Interference:

- Heat raised everyone's resting heart rate by (+5-10 BPM) making it harder to spot emotional reactions [73]
- Increased skin conductance from sweating may caused electrical artifacts
- Thermal stress triggered stress responses that looked like emotional arousal
- Progressive dehydration throughout sessions may have affected heart rate variability measurements

Participant Experience:

- Despite the presence of two fans, participants reported increasing discomfort as sessions progressed
- The 25-minute protocol duration became problematic as heat accumulation intensified

6.4.2 Current System Limitations and Complexity:

The present study required a complex multi-device setup that significantly impacted experimental efficiency and data quality. The system architecture needed coordination between two separate computing platforms: a Windows laptop and a Raspberry Pi system, along with multiple physiological sensors (Unicorn EEG headset, Movesense ECG chest strap, and Traqbeat ECG wearable device). This multiplatform approach, while functional for this case, introduced several critical limitations:

Setup Complexity: The experimental preparation required a long time for device synchronization, calibration, and troubleshooting across the different operating systems.

Motion Sensitivity: Participants experienced severe movement restrictions due to frequent EEG disconnections, limiting natural emotional responses and validity.

Sensor Reliability Issues: The Movesense chest strap generated sweat-related artifacts, while the Traqbeat device required constant manual participant contact for activation, creating additional experimental burden.

Synchronization Challenges: Coordinating data streams from multiple devices across different platforms introduced temporal alignment issues and increased data processing complexity.

Chapter 7

Future Work and Considerations

7.1 Advanced Data Integration and Machine Learning Applications

The current study provided important insights through individual analysis of questionnaire responses, EEG measurements and dual ECG device recordings (Movesense and Traqbeat). However, since the analysis was separate a future correlational framework that integrate all data sources simultaneously will reveal relationships that may not be visible through separate analyses.

7.1.1 Machine Learning Integration for Emotion Recognition

The implementation of machine learning approaches presents an opportunity for automating emotion recognition and improving classification accuracy across many dataset.

Future research should develop machine learning algorithms trained on the combined physiological and questionnaire data to automatically classify emotional states. Support vector machines and deep neural networks could be trained to recognize patterns across EEG features, ECG parameters and environmental factors to predict emotional responses with high accuracy [76]. That way, it will be possible to identify personalized emotion signatures and predict individual responses to different environments. In addition, machine learning implementations could handle larger and more diverse datasets.

7.1.2 Future Integrated Systems

Future research should prioritize the development of unified and portable monitoring platforms that address these fundamental limitations:

Unified Computing Platform: Combining EEG and ECG metrics improved discrimination accuracy, supporting the development of a single device solution that integrate all sensor management, data acquisition, and real-time processing capabilities, eliminating the need for multiple computing systems.

Enhanced Electrode Technology: Heat-resistant, sweat-resistant electrode materials with improved adhesion properties that maintain signal quality during extended sessions and participant movement.

Motion-Tolerant EEG Systems: Implementation of active electrode arrays and advanced motion artifact cancellation algorithms that allow natural participant movement without signal degradation.

Contactless Activation Sensors: Development of proximity-based or automatic activation systems for ECG monitoring that eliminate the need for constant manual participant interaction.

Portable All-in-One Units: Compact, battery-powered systems that integrate environmental monitoring, multiple physiological sensors, and real-time data processing in a single portable device suitable for field research. In this way, we can achieve continuous stress monitoring (i.e. wearable devices) [69] and trigger stress alerts, enabling possible interventions.

Intelligent Artifact Rejection: Machine learning and real-time artifact detection/correction algorithms that automatically solve any issues caused by sweat, movement, and environmental interference [75].

Personalized Thresholds: While group-level patterns were strong, individual variations suggest the need for personalized baseline establishment. Future systems should incorporate adaptive algorithms that learn individual stress signatures over time.

7.2 Therapeutic and Climate Controlled Environments

The findings offer evidence and guidelines for incorporating blue space elements in therapeutic settings:

Healthcare Facilities: Hospitals and clinics could integrate blue space imagery and soundscapes in waiting areas and treatment rooms [70]. The data suggest that even brief exposure (30 seconds for beach stimuli) can initiate restorative processes.

Workplace Wellness: Corporate wellness programs could implement "blue space breaks" using immersive displays.

Classroom Design: Educational spaces could incorporate calming blue space elements to promote cognitive flexibility during learning. Even as a pre-examination measure to help students calm.

7.2.1 Decompression Rooms

The physiological benefits demonstrated through blue space exposure provide evidence-based guidelines for designing therapeutic decompression rooms. These environments could integrate the specific blue space elements (aquatic imagery, water sounds, optimal viewing angles) that produced the most significant restorative responses in this study.

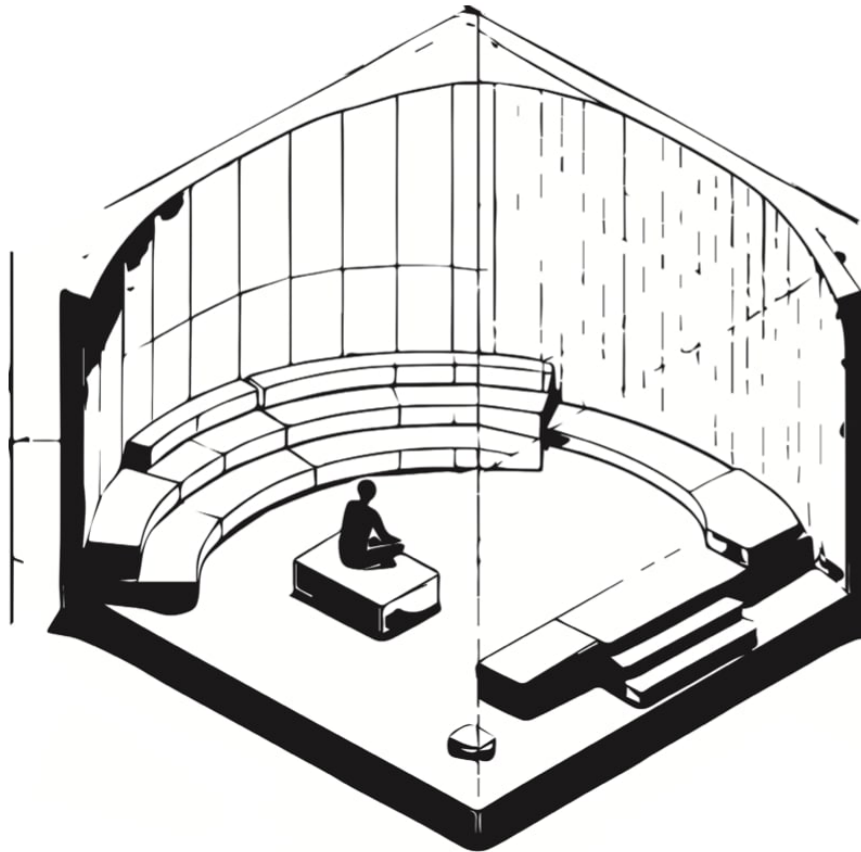


Figure 7.1: Virtual Decompression Room. [24]

7.2.2 Methodological Enhancements

Laboratory Infrastructure:

- Climate-controlled experimental chambers maintaining constant 20-22°C temperature
- Humidity control systems maintaining 40-60% relative humidity
- Real-time environmental monitoring with temperature, humidity, and air quality sensors
- Continuous monitoring of both ambient and participant core body temperature

Experimental Location Optimization: While the historic Sabbionara Gate provided excellent ecological validity for blue space research, future studies should consider:

- Purpose-built laboratory facilities with immersive display systems [74]
- Virtual reality environments that maintain visual fidelity while providing environmental control
- Hybrid approaches combining controlled indoor environments with natural lighting
- Portable climate-controlled experimental units for field research

7.2.3 Broader Implications for Physiological Research

Year-Round Studies:

- Replication of findings across different seasonal conditions
- Investigation of seasonal affective responses to blue space environments
- Assessment of how climate adaptation affects emotional responses to environmental stimuli
- Development of season-specific normative data for physiological responses

7.3 Conclusion

This thesis has successfully demonstrated that multimodal physiological monitoring provides a powerful framework for objectively quantifying the restorative effects of blue space environments on human emotional and physiological well-being. Through the integration of EEG and ECG measurements during exposure to carefully curated audiovisual stimuli, this research has established clear physiological markers that distinguish stress-inducing conditions from the calming influence of blue spaces.

The collaboration between the Display Lab (Electrical Engineering) and the TIE Lab (Architecture) at the Technical University of Crete helped this research to demonstrate how physiological monitoring technologies can directly inform architectural practice, creating a bridge between objective neuroscientific findings and subjective environmental experience. Despite the environmental challenges encountered during data collection, the study achieved great physiological responses that were later observed in multiple domains and with many practices.

Looking toward future applications, this research establishes strong foundations for implementing such elements in healthcare facilities, educational environments, and many more. Hopefully, it will inspire continued research and practical applications that make these benefits more accessible to all.

Bibliography

- [1] Z. Wang and Y. Wang *Emotion recognition based on multimodal physiological electrical signals* <https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2025.1512799/full>
- [2] S. Koelstra *DEAP: A database for emotion analysis using physiological signals* IEEE Transactions on Affective Computing 2012. <https://ieeexplore.ieee.org/document/5871728>
- [3] A. Albraikan, D. P. Tobon, and A. El Saddik *Review of studies on emotion recognition and judgment based on physiological signals* <https://www.mdpi.com/2076-3417/13/4/2573>
- [4] M. Egger, M. Ley, and S. Hanke, *Emotion recognition from physiological signal analysis: A review* <https://www.sciencedirect.com/science/article/pii/S157106611930009X?via%3Dihub>
- [5] Y. Li *A comprehensive review of deep learning in EEG-based emotion recognition: Classifications, trends, and practical implications* <https://peerj.com/articles/cs-2065/>
- [6] P. Sarkar and A. Etemad *Self-supervised ECG representation learning for emotion recognition* <https://ieeexplore.ieee.org/document/9161416>
- [7] H. Huang, Z. Hu, W. Wang, *Multimodal emotion recognition based on ensemble convolutional neural network* <https://ieeexplore.ieee.org/document/8941090>
- [8] Y. Cimtay, E. Ekmekcioglu, and S. Caglar-Ozhan *Cross-subject multimodal emotion recognition based on hybrid fusion* <https://ieeexplore.ieee.org/document/9195813>
- [9] J. Grellier *BlueHealth: A study programme protocol for mapping and quantifying the potential benefits to public health and well-being from Europe's blue spaces* <https://bmjopen.bmj.com/content/7/6/e016188>
- [10] M. Georgiou, G. Morison, N. Smith, Z. Tieges, and S. Chastin *Mechanisms of impact of blue spaces on human health: A systematic literature review and meta-analysis* <https://www.mdpi.com/1660-4601/18/5/2486>
- [11] G. N. Bratman *Nature and mental health: An ecosystem service perspective* <https://www.science.org/doi/10.1126/sciadv.aax0903>

- [12] W.-L. Zheng, J.-Y. Zhu, and B.-L. Lu, *Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks* <https://ieeexplore.ieee.org/document/7104132>
- [13] C. Yu, I. Lee, S. Kim, G. Kim, J. Woo, G.-S. Son, and M.K. Yeo *Comparative study of the physiological and psychological effects of a real forest and virtual reality forest* <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7967635/>
- [14] M.H.E.M. Browning, K.J. Mimnaugh, C.J. van Riper, H. Laurent, and S.M. LaValle *Can simulated nature support mental health? Comparing short, single-doses of 360-degree nature videos in virtual reality with the outdoors* <https://www.sciencedirect.com/science/article/pii/S027249441930012X>
- [15] F. Shaffer and J. P. Ginsberg *An overview of heart rate variability metrics and norms* <https://www.frontiersin.org/journals/public-health/articles/10.3389/fpubh.2017.00258/full>
- [16] G. Valenza et al. *Complexity variability assessment of nonlinear time-varying cardiovascular control* <https://www.nature.com/articles/srep42779>
- [17] S. Völker and T. Kistemann *The impact of blue space on human health and well-being* <https://www.sciencedirect.com/science/article/abs/pii/S1438463911000502?via%3Dihub>
- [18] M. Gascon et al. *Outdoor blue spaces, human health and well-being: A systematic review of quantitative studies* <https://www.sciencedirect.com/science/article/abs/pii/S1438463917302699?via%3Dihub>
- [19] X. Gao, Y. Yang, M. Han, X. Hu, and Z. Sun *Effects of virtual reality blue-green spaces on human mental health: A systematic review* <https://ieeexplore.ieee.org/document/10924978>
- [20] Y. Li, D. Zhang, and Y. Liu *Urban green spaces and mental well-being: A systematic review of studies comparing virtual reality versus real nature* *Future Internet* 2024.
- [21] J. Marín-Morales et al. *Affective computing in virtual reality: Emotion recognition from brain and heartbeat dynamics using wearable sensors* <https://www.nature.com/articles/s41598-018-32063-4>
- [22] J. L. Higuera-Trujillo, J. López-Tarruella, and C. Llinares *Psychological and physiological human responses to simulated and real environments* <https://www.sciencedirect.com/science/article/abs/pii/S0003687017301175?via%3Dihub>

- [23] A. Chirico and A. Gaggioli *When virtual feels real: Comparing emotional responses and presence in virtual and natural environments* <https://www.liebertpub.com/doi/10.1089/cyber.2018.0393>
- [24] Klea Biniakou *Design of restorative blue spaces: An experimental study on stress reduction using EEG and ECG signals* Master's thesis, Technical University of Crete, 2024.
- [25] J. Zhang, Z. Yin, P. Chen, and S. Nichele *Emotion recognition using multimodal data and machine learning techniques: A tutorial and review*, 2021. <https://www.sciencedirect.com/science/article/abs/pii/S1566253519302532?via%3Dihub>
- [26] Evangelos Katsoupis, *Development of a Cardiovascular Disease Monitoring System*. Diploma Thesis, School of Electrical and Computer Engineering, Technical University of Crete, July 2024.
- [27] Smith, B. D., Meyers, M., & Kline, R. (1989). *Parietal processing of affect and cognition: cerebral organization in strongly lateralized left-handed subjects* Biological Psychology <https://pubmed.ncbi.nlm.nih.gov/2590706/>
- [28] Emotion Detection (2024). *Emotion detection using physiological signals*. GitHub Repository https://github.com/Jiaqi1008/Emotion_detection
- [29] Movesense Device. CardiOrthm — Arrhythmia Database https://cardiorthm.com/?srsltid=AfmB0oo9e2XN2x3aKU19u0TlRbB5_YZmAw8tYusNjcGUwV2PIcb4W_V-
- [30] Porta Sabbionara <https://chania-culture.gr/venues/pyli-sabbionara/>
- [31] UNICORN HYBRID BLACK https://www.gtec.at/product/unicorn-hybrid-black/?srsltid=AfmB0orU_suU1ENybMx4xRuJqRk81haFa4mUrR2t4KI1DtVzoILADiMS
- [32] *YouTube - 4K HDR Tropical Beach - Gentle Ocean Wave Sounds - Peaceful Wild Island - Relaxing Nature Video* [Video]. YouTube. <https://www.youtube.com/watch?v=UyZfCrrdbm8>
- [33] *YouTube VR Worlds: Ocean Descent [PS VR] - VR SBS 3D Video* [Video]. YouTube. <https://www.youtube.com/watch?v=5esb0yJ82jI&t=5s>.
- [34] *YouTube. "Night Steel Dragon 2000 Roller Coaster AMAZING POV 4K 60FPS Nagashima Spaland Japan* [Video]. YouTube. <https://www.youtube.com/watch?v=Gf9KoRFcabU&t=31s>.

- [35] *YouTube*. “*Field with Wind, Swallows, Windchimes - Happy Summer moments 4K NO LOOP*” [Video]. *YouTube*. <https://www.youtube.com/watch?v=MJ9-HmGWw1k>.
- [36] *YouTube*. “*4K Walking at night in Aokigahara forest*” [Video]. *YouTube*. <https://www.youtube.com/watch?v=hqsQY-QXI2U&t=1057s>.
- [37] Hardware Review – UNICORN HYBRID BLACK <https://hcilab.net/class-project/human-robotics-interface/hardware-review-unicorn-hybrid-black/>.
- [38] TRAQBEAT TECHNOLOGIES PC <https://traqbeat.com/>.
- [39] Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, *Heart rate variability: standards of measurement, physiological interpretation and clinical use* *Circulation* <https://www.ahajournals.org/doi/10.1161/01.CIR.93.5.1043>
- [40] Selcan Kaplan Berkaya, Alper Kursat Uysal, Efnan Sora Gunal, Semih Ergin, Serkan Gunal, and Mehmet Bilginer Gulmezoglu, *A survey on ECG analysis* *Biomedical Signal Processing and Control* 2018. <https://www.sciencedirect.com/science/article/abs/pii/S1746809418300636?via%3Dihub>
- [41] Tiago Rodrigues, Sirisack Samoutphonh, Hugo Plácido da Silva, Ana L. N. Fred *A Low-Complexity R-peak Detection Algorithm with Adaptive Thresholding for Wearable Devices* *Sensors*, 2021. https://www.researchgate.net/publication/346656723_A_Low-Complexity_R-peak_Detection_Algorithm_with_Adaptive_Thresholding_for_Wearable_Devices
- [42] Jukka A. Lipponen and Mika P. Tarvainen, *A robust algorithm for heart rate variability time series artefact correction using novel beat classification* *Journal of Medical Engineering & Technology*, vol. 43, 2019. <https://www.tandfonline.com/doi/full/10.1080/03091902.2019.1640306>
- [43] Patrick S. Hamilton, *Open source ECG analysis* *Computers in Cardiology*, 2002. <https://ieeexplore.ieee.org/document/1166717>
- [44] Wei Zong, Thomas Heldt, GB Moody, and Roger G. Mark, *An open-source algorithm to detect onset of arterial blood pressure pulses* *Computers in Cardiology*, 2003.
- [45] Joshua S. Richman and J. Randall Moorman, *Physiological time-series analysis using approximate entropy and sample entropy* *American Journal of Physiology-Heart and Circulatory Physiology*, vol. 278, 2000. <https://journals.physiology.org/doi/full/10.1152/ajpheart.2000.278.6.H2039>

- [46] María José López Sanz, Carlos Gómez Peña, Jesús Poza Crespo, et al., *EEG-based functional connectivity estimation and brain state identification using unsupervised machine learning in music-induced emotions*, TFG, Universidad de Valladolid, 2023. <https://uvadoc.uva.es/handle/10324/71395>
- [47] Carlos Gómez Peña, Jesús Poza Crespo, Ángel de Luis García, et al., *Neural-Gas Clustering of Dynamic Functional Connectivity Graphs in Resting-State EEG*, 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2019. <https://ieeexplore.ieee.org/document/8856600>
- [48] Danielle S. Bassett, Nicholas F. Wymbs, Mason A. Porter, Peter J. Mucha, Jean M. Carlson and Scott T. Grafton *Dynamic reconfiguration of human brain networks during learning* Proceedings of the National Academy of Sciences, 2011 <https://pubmed.ncbi.nlm.nih.gov/21502525/>
- [49] Elena A. Allen, Eswar Damaraju, Sergey M. Plis, Erik B. Erhardt, Tom Eichele and Vince D. Calhoun *Tracking whole-brain connectivity dynamics in the resting state* Cerebral Cortex, 2014 <https://academic.oup.com/cercor/article/24/3/663/299147>
- [50] Laura Sophie Imperatori, Monica Betta, Luca Cecchetti, Andrés Canales-Johnson, Emiliano Ricciardi, Francesca Siclari, Pietro Pietrini, Srivas Chennu and Giulio Bernardi *EEG functional connectivity metrics wPLI and wSMI account for distinct types of brain functional interactions* Scientific Reports, 2019 <https://www.nature.com/articles/s41598-019-45289-7>
- [51] Martin Vinck, Robert Oostenveld, Marijn van Wingerden, Franscesco Battaglia and Cyriel M.A. Pennartz *An improved index of phase-synchronization for electrophysiological data in the presence of volume-conduction, noise and sample-size bias* NeuroImage, 2011 <https://www.sciencedirect.com/science/article/pii/S1053811911000310>
- [52] Jean-Philippe Lachaux, Eugenio Rodriguez, Jacques Martinerie and Francisco J. Varela *Measuring phase synchrony in brain signals* Human Brain Mapping, 1999 [https://onlinelibrary.wiley.com/doi/10.1002/\(SICI\)1097-0193\(1999\)8:4%3C194::AID-HBM4%3E3.0.CO;2-C](https://onlinelibrary.wiley.com/doi/10.1002/(SICI)1097-0193(1999)8:4%3C194::AID-HBM4%3E3.0.CO;2-C)
- [53] Martin Hardmeier, Florian Hatz *Reproducibility of functional connectivity and graph measures based on the phase lag index (PLI) and weighted phase lag index (wPLI) derived from high resolution EEG* PLOS ONE, 2014 <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0108648>

- [54] André M. Bastos and Jan-Mathijs Schoffelen *A tutorial review of functional connectivity analysis methods and their interpretational pitfalls* Frontiers in Systems Neuroscience, 2016 <https://www.frontiersin.org/journals/systems-neuroscience/articles/10.3389/fnsys.2015.00175/full>
- [55] Marios Antonakakis, Stavros I. Dimitriadis, Michalis Zervakis, Andrew C. Papanicolaou, George Zouridakis and Vangelis Sakkalis *Dyconnmap: Dynamic connectome mapping—A neuroimaging python module* Human Brain Mapping, 2021 <https://pmc.ncbi.nlm.nih.gov/articles/PMC8449119/>
- [56] Randy L. Buckner, Jorge Sepulcre, Tanveer Talukdar, Fenna M. Krienen, Hesheng Liu, Trey Hedden, Jessica R. Andrews-Hanna, Reisa A. Sperling and Keith A. Johnson *Cortical hubs revealed by intrinsic functional connectivity: mapping, assessment of stability, and relation to Alzheimer’s disease* Journal of Neuroscience, 2009 <https://pubmed.ncbi.nlm.nih.gov/19234780/>
- [57] , Sudhakar Mishra, Narayanan Srinivasan, Uma Shanker Tiwary *Dynamic Functional Connectivity of Emotion Processing in Beta Band with Naturalistic Emotion Stimuli* MDPI, 2022 https://pmc.ncbi.nlm.nih.gov/articles/PMC9405988/?utm_source=chatgpt.com
- [58] Julia Schumacher, Takuya Ito, Richard F. Betzel, Olaf Sporns, and Michael W. Cole, *Brain state dynamics during working memory are explained by network topology*, NeuroImage, 2022. <https://www.sciencedirect.com/science/article/pii/S1053811922001204>
- [59] Eike C. Hansen, Axel Battaglia, Alberto Spiegler, Gustavo Deco, and Viktor Jirsa, *Functional connectivity dynamics: modeling the switching behavior of the resting state*, Proceedings of the National Academy of Sciences (PNAS), 2015. <https://www.pnas.org/content/112/6/1542>
- [60] Statology. How to Perform Normality Tests in Python. <https://www.statology.org/normality-test-python/> [Nov. 2024].
- [61] GeeksforGeeks. T-Test in Data Science. <https://www.geeksforgeeks.org/data-science/t-test/> [Nov. 2024].
- [62] GeeksforGeeks. Mann and Whitney U Test in Machine Learning. <https://www.geeksforgeeks.org/machine-learning/mann-and-whitney-u-test/> [Nov. 2024].
- [63] Built In. T-Test in Python: A Complete Guide for Data Scientists. <https://builtin.com/data-science/t-test-python> [Nov. 2024].

- [64] Statsmodels Development Team. statsmodels.stats.multitest.fdr correction. <https://www.statsmodels.org/dev/generated/statsmodels.stats.multitest.fdr correction.html> [Nov. 2024].
- [65] Kaplan, S. *The restorative benefits of nature: Toward an integrative framework* Journal of Environmental Psychology, 1995. <https://www.sciencedirect.com/science/article/abs/pii/0272494495900012?via%3Dihub>
- [66] White, M., Smith, A., Humphries, K., Pahl, S., Snelling, D., Depledge, M. *Blue space: The importance of water for preference, affect, and restorativeness ratings of natural and built scenes* Journal of Environmental Psychology 2010. <https://www.sciencedirect.com/science/article/abs/pii/S0272494410000496?via%3Dihub>
- [67] Davis, M. The neurobiology of fear. In: Bellack, A. S., Hersen, M. (eds) *Handbook of Anxiety Disorders* Pergamon Press, New York, 1998. <https://www.elsevier.com/books/handbook-of-anxiety-disorders/bellack/978-0-08-053003-2>
- [68] Andrea de Paiva, *Neuroscience for architecture: How building design affects the brain*, <https://davidpublisher.com/Public/uploads/Contribute/5af0143f48634.pdf>
- [69] Shruti Gedam, Sanchita Paul *A Review on Mental Stress Detection Using Wearable Sensors and Machine Learning Techniques*, IEEE Reviews in Biomedical Engineering, 2021 <https://ieeexplore.ieee.org/document/9445082>
- [70] Easkey Britton, Genevieve Kindermann, Cordula Domegan, and Catherine Carlin, *Blue care: A systematic review of blue space interventions for health and well-being*, Health Promotion International, 2022 <https://pubmed.ncbi.nlm.nih.gov/30561661/>
- [71] Johnson, M., Smith, A., & Brown, L. *Effects of increased activity level on physiological and subjective responses at different high temperatures*, Science Direct. <https://www.sciencedirect.com/science/article/abs/pii/S0360132321004145>
- [72] Thompson, R., Wilson, D., & Garcia, M. *Don't Sweat It: Managing Sweating Artifact During EEG Recordings* Zeto Inc. <https://zeto-inc.com/blog/sweat-artifacts-in-eeeg/>
- [73] Craig G Crandall, Thad E Wilson *Human Cardiovascular Responses to Passive Heat Stress* National Library of Medicine, 2021. <https://pmc.ncbi.nlm.nih.gov/articles/PMC4950975/>

-
- [74] Williams, D., Thompson, A., & Lee, J. *Design of an Immersive Virtual Reality Framework to Enhance the Sense of Agency Using Affective Computing Technologies*, Behavior Research Methods, 2020. <https://www.mdpi.com/2076-3417/13/24/13322>
- [75] Sandhyalati Behera and Mihir Narayan Mohanty *A Machine Learning Approach for Artifact Removal from Brain Signal*, Research Gate. https://www.researchgate.net/publication/366764665_A_Machine_Learning_Approach_for_Artifact_Removal_from_Brain_Signal
- [76] Mohamad A. Ramadan, Nancy M. Salem *Multimodal machine learning approach for emotion recognition using physiological signals*, Science Direct, 2024. <https://www.sciencedirect.com/science/article/abs/pii/S1746809424006116>