

DOTTORATO DI RICERCA IN
INGEGNERIA DELL'INFORMAZIONE

CICLO XXXVIII - PNRR NextGenerationEU

*Multimodal Neurophysiological and
Behavioral Modeling of
Psychofunctional Human States Across
Contexts*

Settore Scientifico Disciplinare

ING-INF/06

Dottorando

Dott./Dott.ssa (*Cognome e Nome*)

Tarchi Pietro

Supervisore

Prof./Prof.ssa (*Cognome e Nome*)

Lanatà Antonio

Coordinatore

Prof./Prof.ssa (*Cognome e Nome*)

¹
Ricci Stefano



UNIVERSITÀ
DEGLI STUDI
FIRENZE

UNIVERSITÀ DEGLI STUDI DI FIRENZE
DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE (DINFO)
CORSO DI DOTTORATO IN INGEGNERIA DELL'INFORMAZIONE
CURRICULUM: AUTOMATICA, OTTIMIZZAZIONE E SISTEMI
COMPLESSI (AOSC)

MULTIMODAL NEUROPHYSIOLOGICAL AND BEHAVIORAL MODELING OF
PSYCHOFUNCTIONAL HUMAN STATES ACROSS CONTEXTS

Candidate

Pietro Tarchi

Supervisors

Prof. Antonio Lanata

Dr. Claudio Gentili

Dr. Danilo Menicucci

PhD Coordinator

Prof. Stefano Ricci

CICLO XXXVIII, 2023-2025

Università degli Studi di Firenze, Dipartimento di Ingegneria
dell'Informazione (DINFO).

Thesis submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Information Engineering. Copyright © 2026 by
Pietro Tarchi.

A XXXXX

Acknowledgments

I would like to acknowledge the efforts and input of my supervisor, Prof. Antonio Lanatà, and all my colleagues of the Computational Physiology and Biomedical Systems (ComPBioS) group who were of great help during my research. In particular my thanks go to Ph.D. Lorenzo Frassinetti, Eng. Federico Calà and Ph.D. Mustafa Can Gursesli who collaborated on the main parts of my research work. I would like to thank also Prof. Elísio Costa and Prof. Antonio Coelho for their kind support and hospitality during my stay at Porto.

List of Acronyms

- **ADHD** – Attention-Deficit/Hyperactivity Disorder
- **AI** – Artificial Intelligence
- **AIC** – Akaike Information Criterion
- **AE** – Affective Empathy
- **AmpEnv** – Amplitude Envelope
- **ANS** – Autonomic Nervous System
- **AR** – Autoregressive
- **ARMA** – Autoregressive Moving Average
- **AS** – Active Sessions
- **ASD** – Autism Spectrum Disorder
- **BA** – Broca Area
- **BCT** – Brain Connectivity Toolbox
- **BF** – Biofeedback
- **BIC** – Bayesian Information Criterion
- **CAR** – Common Average Reference
- **CE** – Cognitive Empathy
- **CNNs** – Convolutional Neural Networks
- **CNS** – Central Nervous System
- **CV** – Computer Vision
- **DFA** – Detrended Fluctuation Analysis
- **ECG** – Electrocardiography
- **EDA** – Electrodermal Activity
- **EEG** – Electroencephalography

- **EMG** – Electromyography
- **ER** – Entropy Rate
- **ERPs** – Event-Related Potentials
- **F** – Female
- **FAA** – Frontal Alpha Asymmetry
- **FACS** – Facial Action Coding System
- **FCSTMs** – False-Colors Scalp Topographic Maps
- **FFA** – Fusiform Face Area
- **FFT** – Fast Fourier Transform
- **FG** – Fusiform Gyrus
- **FER** – Facial Emotion Recognition
- **fMRI** – functional Magnetic Resonance Imaging
- **fNIRS** – functional Near-Infrared Spectroscopy
- **FNN** – False Nearest Neighbors
- **FS** – Fantasy Scale
- **FP** – Face Processing
- **FR** – Face Recognition
- **GANs** – Generative Adversarial Networks
- **GEEs** – Generalized Estimating Equations
- **GLM** – Generalized Linear Model
- **GLMMs** – Generalized Linear Mixed Models
- **GP** – Game Performance
- **GSR** – Galvanic Skin Response
- **HAHV** – High Arousal High Valence

- **HALV** – High Arousal Low Valence
- **HD** – High-Definition or High-Density
- **HF** – High-Frequency
- **HAPPE** – Harvard Automated Processing Pipeline for EEG
- **HMMs** – Hidden Markov Models
- **HR** – Heart Rate
- **HRV** – Heart Rate Variability
- **HS** – Hyperscanning
- **IAPS** – International Affective Picture System
- **IBS** – Inter-Brain Synchrony or Synchronisation
- **ICA** – Independent Component Analysis
- **IHR** – Instantaneous Heart Rate
- **INS** – Interpersonal Neural Synchronisation
- **IQR** – Interquartile Range
- **IRF** – Impulse Response Function
- **IRI** – Interpersonal Reactivity Index
- **LAHV** – Low Arousal High Valence
- **LALV** – Low Arousal Low Valence
- **LF** – Low-Frequency or Left Frontal
- **LPFC** – Left Prefrontal Cortex
- **LQ** – Laterality Quotient
- **LTC** – Left Temporal Cortex
- **LTO** – Left Temporo-Occipital
- **LLE** – Largest Lyapunov Exponent

- **M** – Male
- **MAD** – Median Absolute Deviation
- **MAP** – Maximum a Posteriori
- **MARA** – Multiple Artifact Rejection Algorithm
- **MC** – Markov Chains
- **MCI** – Mild Cognitive Impairment
- **MEG** – Magnetoencephalography
- **MHT** – Mean Hitting Time
- **ML** – Machine Learning
- **NA** – Negative Affect
- **NOBF** – No Biofeedback
- **NDDs** – Neurodevelopmental Disorders
- **NF** – Neurofeedback
- **NS** – Nervous System, Non Significant or Neutral Sessions
- **NSSCRs** – Non-Specific Skin Conductance Responses
- **PA** – Positive Affect
- **PAA** – Parietal Alpha Asymmetry
- **PANAS** – Positive and Negative Affect Schedule
- **PCHIP** – Piecewise Cubic Hermite Interpolating Polynomial
- **PD** – Personal Distress, Pupil Diameter or Pupil Dilation
- **PDF** – Probability Density Function
- **PLI** – Phase Lag Index
- **PLV** – Phase Locking Value
- **PNS** – Peripheral Nervous System

- **PSD** – Power Spectral Density
- **PSNS** – Parasympathetic Nervous System
- **PT** – Perspective Taking
- **PWs** – Pseudowords
- **QCAE** – Questionnaire of Cognitive and Affective Empathy
- **RF** – Right Frontal
- **RH** – Right Hemisphere
- **RMS** – Root Mean Square
- **ROIs** – Regions of Interest
- **RPFC** – Right Prefrontal Cortex
- **RQA** – Recurrent Quantification Analysis
- **RTC** – Right Temporal Cortex
- **RTO** – Right Temporo-Occipital
- **SAM** – Self-Assessment Manikin
- **SampEn** – Sample Entropy
- **SB** – Streak Bonus
- **SC** – Skin Conductance
- **SCR** – Skin Conductance Response
- **SCL** – Skin Conductance Level
- **SCp** – Sub-Chain Probability
- **SGs** – Serious Games
- **SIAS** – Social Interaction Anxiety Scale
- **SD/STD** – Standard Deviation
- **SDNN** – Standard Deviation of NN Intervals

- **SLDs** – Speech and Language Disorders
- **SMNA** – Sudomotor Nerve Activity
- **SNS** – Sympathetic Nervous System
- **SpG** – Spectral Gap
- **SPS** – Social Phobia Scale
- **St** – Stability
- **STMs** – Scalp Topographic Maps
- **STS** – Superior Temporal Sulcus
- **TAS 20** – Toronto Alexithymia Scale
- **TB** – Time Bonus
- **TCM** – Transition Co-Occurrence Matrix
- **TPJ** – Temporo-Parietal Junction
- **TS** – Text Strings
- **VLF** – Very-Low-Frequency
- **VR** – Virtual Reality
- **Ws** – Words
- **WA** – Wernike Area
- **WAFER** – Web-Agile Facial Emotion Recognition
- **W-ICA** – Wavelet Independent Component Analysis
- **WPWAR** – Words and Pseudowords Aloud Reading
- **WTC** – Wavelet Transform Coherence
- **ZCR** – Zero Crossing Rate

Abstract

The articulation of how cognitive, affective and social processes emerge from the coordinated activity of neural and autonomic systems remains a central question in contemporary neuroscience and affective computing. This dissertation addresses this issue through a series of multimodal experimental studies that progressively move from controlled individual paradigms to ecologically valid, interactive and dyadic contexts. By integrating central measures with autonomic indices and behavioural and psychometric assessments, the work delineates a structure showing how psychophysiological responses evolve as task demands, emotional involvement and social context increase. The first part focuses on controlled perceptual and linguistic scenarios, demonstrating that stimulus authenticity, familiarity and semantic structure systematically modulate early neural dynamics and autonomic responses. Results show that the brain differentiates real versus artificial faces and words versus pseudowords at early processing stages, through distinct spectral and event-related patterns, while peripheral markers reflect differences in cognitive effort and arousal. The second part extends the investigation to naturalistic, goal-directed gaming scenarios, where participants engage in cognitively demanding tasks across different cultural populations. Multimodal analyses combining electroencephalography (EEG), pupillometry, cardiovascular dynamics and facial expressions reveal that task performance is shaped by the interplay between cognitive load, emotional regulation and autonomic adaptability. High performance is associated with efficient neural modulation and stable emotional dynamics, whereas lower performance corresponds to increased cognitive load and less regulated affective responses. The final part explicitly addresses the affective and interpersonal dimension of psychophysiological processing. Starting from individual neuroaesthetic experience, the work shows that art expertise and dispositional empathy differentially modulate large-scale brain connectivity over time. This individual-level perspective is then extended to dyadic settings, where shared affective stimulation elicits partial convergence of autonomic responses even in the absence of explicit interaction. Finally, EEG hyperscanning with biofeedback demonstrates that inter-brain synchronisation emerges as a dynamic and trait-dependent process, shaped by both individual characteristics and their relational configuration within the dyad. These studies offer conceptual and methodological advances by integrating controlled laboratory paradigms with interaction-rich experimental designs. They demonstrate that cognitive mechanisms, affective

modulation and social resonance are not separable layers but mutually constraining processes expressed through coordinated central-autonomic patterns. Beyond its theoretical contribution, this work expands current knowledge in affective computing, providing a foundation for future developments in clinical assessment, cognitive training and socially adaptive technologies.

Contents

Contents	xiii
1 Introduction	1
1.1 Background and Rationale	2
1.2 Objectives and Structure of the Thesis	4
1.2.1 Structure of the Thesis	5
2 Theoretical and Methodological Framework	9
2.1 Physiological Basis of Human Nervous System	10
2.1.1 Physiological Markers of Cognitive and Emotional State	12
2.2 Characteristics of Biomedical Signals	14
2.2.1 Deterministic and stochastic characteristics	15
2.2.2 Stationarity, variability, and complexity	17
2.2.3 From linear to nonlinear and dynamical analysis . . .	17
2.2.4 Methodological implications and acquisition chain . .	18
2.3 Electroencephalography (EEG)	19
2.3.1 EEG Preprocessing: The HAPPE Workflow	19
2.3.2 ERP Analysis	22
2.3.3 Spectral Power Analysis	23
2.3.4 Functional Connectivity: Phase Lag Index (PLI) . . .	24
2.3.5 Hyperscanning: Frontal Alpha Asymmetry, Laterality Quotient and Phase Locking Value	27
2.4 Electrodermal Activity (EDA)	28
2.4.1 EDA Analysis	29
2.4.2 EDA Decomposition: the cvxEDA Algorithm	29
2.4.3 EDA Features	31

2.4.4	Nonlinear Complexity Analysis: Phase Space Reconstruction, Sample Entropy, and ComEDA	34
2.5	ECG and Heart Rate Variability Analysis Methodology	36
2.5.1	R-Peak Detection: the Pan–Tompkins Algorithm	36
2.5.2	Point-Process Modeling for Continuous HRV Reconstruction	37
2.6	Pupillometry Data Analysis	38
2.6.1	Pupillometric Feature Extraction	39
2.7	Markov-Inspired Approach for Facial Expressions Dynamic Analyses	40
2.8	Data Acquisition Systems	42
2.8.1	EEG Systems	43
2.8.2	Autonomic Nervous System Systems	44
2.8.3	Pupillometry, Voice and Facial Expression Data	44
2.8.4	Synchronization Infrastructure	46
2.8.5	Data Management and Processing	47
2.9	Psychological Assessment Tools	48
3	Neurophysiological Responses to Natural and Non-Natural Stimuli: From Faces to Lexical Units	53
3.1	Real and Deepfake Face Recognition an EEG Study on Cognitive and Emotive Implications	55
3.1.1	Introduction	55
3.1.2	Materials and Methods	58
3.1.3	Results	64
3.1.4	Discussion	70
3.2	Multimodal Neurophysiological Correlates of Word and Pseudoword Processing	74
3.2.1	Introduction	74
3.2.2	Experimental set-up	77
3.2.3	EEG Analyses	79
3.2.4	EDA and Voice Analysis	84
3.3	Conclusions	88
4	Multimodal Cognitive and Affective Dynamics in Game-Based Tasks	91
4.1	Materials	93
4.1.1	Participants and Experimental Paradigm	93

4.1.2	Physiological Recordings	94
4.1.3	Snake Game	95
4.1.4	Matching Pairs Game	96
4.2	EEG Markers and Affective Evaluation of Engagement and Performance in the Snake Game	98
4.2.1	Introduction	98
4.2.2	Materials and Methods	100
4.2.3	Results	102
4.2.4	Discussions	105
4.3	Pupil Dilation Dynamics in Matching Pairs Game Emotional Activation	108
4.3.1	Introduction	108
4.3.2	Materials and Methods	110
4.3.3	Results	111
4.3.4	Discussions	112
4.4	Multimodal Analysis of Emotions in Gaming: Understanding Cultural Influences	114
4.4.1	Introduction	114
4.4.2	Related Studies and Study Structure	120
4.4.3	Materials and Methods	125
4.4.4	Results	130
4.4.5	Discussion	137
4.4.6	Implications, Future Studies and Limitations	144
4.5	Conclusions	146
5	Integrated Affective Neuroscience Across Individual and Dyadic Contexts: From Neuroaesthetic Processing to Interpersonal Synchrony	149
5.1	Temporal Dynamics of Functional Connectivity during Neu- roaesthetic Experience: Effects of Art Expertise and Psycho- logical Traits	151
5.1.1	Introduction	151
5.1.2	Materials and Methods	153
5.1.3	Results	156
5.1.4	Discussion	160
5.2	Quantitative Electrodermal Activity Analysis of Simultaneous Recordings from Dyads during Affective Visual Task	163
5.2.1	Introduction	163

5.2.2	Material and Methods	164
5.2.3	Results	168
5.2.4	Discussions	170
5.3	Brain-to-brain Emotional Interaction Dynamics under Cross- Biofeedback EEG Hyperscanning	172
5.3.1	Introduction	172
5.3.2	Material and Methods	174
5.3.3	Results	184
5.3.4	Discussions	190
5.4	Conclusions	195
6	Conclusion	197
6.1	Summary of contribution	197
6.2	Cross cutting limitations and implications	201
6.3	Directions for future work	201
A	Appendix	207
A.1	Supplementary Materials of chapter 3	207
A.2	Supplementary Materials of chapter 4	210
B	Publications	215
	Bibliography	219

Chapter 1

Introduction

Over the past three years of doctoral research, this work has been driven by a central scientific question: *how do human emotional, cognitive, and regulatory processes interact to produce coherent patterns of psychophysiological activity?* Addressing this question requires moving beyond the traditional separation among of emotion, cognition, and physiology and instead embracing the view that these dimensions form an intrinsically integrated system. Psychophysiological dynamics emerge from the continuous interplay between central neural activity, autonomic regulation, behavior, and contextual factors. However, despite decades of research across neuroscience, biomedical engineering, and psychology, a comprehensive framework capable of characterizing these interactions across different levels of complexity remains elusive. Each discipline offers partial yet valuable perspectives: neuroscience focuses on neural mechanisms, psychology on clinical and behavioral correlates, and biomedical engineering on quantitative models and computational tools. This thesis aims to bridge these perspectives by developing and applying a multimodal, experimentally grounded, and analytically rigorous approach to the study of human psychofunctional states.

To this end, the research presented here follows a progressive logic, intentionally moving from simple and tightly controlled perceptual conditions to more complex affective, cognitive, and social contexts. This progression is motivated by the idea that understanding how internal states unfold requires examining them at multiple levels of organization, from basic sensory responses to scenarios involving active task engagement, emotional appraisal, and interpersonal modulation. The work, therefore, seeks not

merely to study isolated mechanisms but to elucidate how psychophysiological processes evolve as contextual demands increase. From an engineering standpoint, the central challenge is to translate inherently subjective and intangible mental processes into quantifiable physiological indicators that can be modeled and objectively interpreted. Throughout this doctoral work, this challenge took shape through the design of controlled laboratory experiments and the development of analytical workflows to capture the temporal, nonlinear, and context-dependent dynamics of the human body-mind system. This engineering perspective is complemented by a broader scientific motivation of understanding how psychophysiological activity evolves across different levels of complexity. Wearable and multimodal sensing technologies now allow the collection of neural, autonomic, and behavioral data with increasing ecological validity, enabling the study of cognitive and emotional processes outside strictly controlled laboratory settings. Such technologies open opportunities for continuous and personalized monitoring of mental well-being, cognitive performance, and social interaction, thereby aligning biomedical engineering with human-centered neuroscientific applications. This thesis is therefore the result of an evolving process of integration, both conceptual and methodological. It reflects an attempt to integrate theoretical models, advanced analytical tools, and multimodal physiological measurements within a coherent experimental progression. The work advances the premise that no single dimension can fully account for the richness of human psychophysiological functioning. Instead, meaningful understanding emerges from the interplay of these dimensions across contexts that vary in perceptual, cognitive, affective, and interpersonal complexity. It embodies both a scientific trajectory and a personal research journey, rooted in the belief that the quantitative study of emotion and cognition can address not only fundamental questions in neuroscience and psychology, but also practical needs in human-technology interaction and mental health assessment. The following sections elaborate on the theoretical foundations of this perspective and introduce the methodological and narrative framework that organizes the subsequent chapters.

1.1 Background and Rationale

The study of human psychophysiological functioning lies at the intersection of biomedical engineering, neuroscience, and psychology. Its central aim

is to understand how neural activity, autonomic regulation, and behavioral processes interact to generate emotional and cognitive states. This interdisciplinary field provides a conceptual bridge between subjective experience and objective physiological measurement, enabling the investigation of how internal mental processes are expressed through quantifiable biosignals. Despite extensive progress, characterizing these interactions in a coherent and context-sensitive manner remains one of the key challenges in contemporary human neuroscience.

Early theoretical models laid the conceptual foundation for linking bodily responses to psychological phenomena. The James-Lange theory [212] proposed that emotions arise from the perception of physiological changes, whereas the Cannon-Bard model [31, 68, 69] argued that emotional experience and physiological arousal occur simultaneously and independently. The two-factor theory by Schachter and Singer [380] later emphasized the role of cognitive appraisal in assigning emotional meaning to physiological activation. These classical theories, though heterogeneous, highlight the longstanding scientific effort to understand how the body contributes to emotional and cognitive experience. Contemporary perspectives have shifted toward more integrative and constructivist accounts. The neurovisceral integration model [429] posits that cognitive and affective regulation depend on the coordinated action of distributed neural networks and autonomic pathways. Barrett's theory of constructed emotion [34] similarly highlights the role of interoception, prediction, and conceptual interpretation in shaping affective states. Complementary insights from affective neuroscience show substantial overlap between neural circuits involved in emotion and cognition [107, 258, 259, 338], supporting dynamic and multidimensional rather than categorical models of internal states.

Within this modern framework, a major challenge is to link measurable physiological signals with subjective psychological states in a reproducible, interpretable, and context-sensitive manner. Traditional self-report measures, such as questionnaires, interviews, and rating scales, provide direct access to subjective experience but suffer from intrinsic limitations. They rely on introspection, linguistic formulation, and memory, and are susceptible to contextual biases, expectation effects, and social desirability [132, 300, 341]. Moreover, they often fail to capture the rapid temporal fluctuations characteristic of emotional and cognitive processes. Physiological measures offer a complementary route by providing continuous, objective indicators of cen-

tral and autonomic nervous system activity. Biosignals such as electroencephalography (EEG), electrodermal activity (EDA) and heart rate variability (HRV) – derived from electrocardiography (ECG) – quantify arousal, cognitive workload, and emotional engagement with high temporal resolution [63, 240]. Advances in wearable sensing and multimodal data acquisition further enhance ecological validity, enabling the study of internal states in naturalistic or semi-naturalistic settings. These developments open opportunities for real-time assessment, adaptive feedback systems, and personalized monitoring. However, physiological signals are not direct readouts of discrete psychological constructs. Their interpretation requires theoretical grounding, contextual knowledge, and often the integration of multiple modalities. Multimodal approaches combining self-report, neural, autonomic, and behavioral data are therefore increasingly recognized as essential for obtaining comprehensive and ecologically meaningful representations of human affective and cognitive dynamics. In light of these theoretical and methodological considerations, the present thesis adopts a progressive, multi-layered approach to the investigation of human psychophysiological functioning. Rather than treating emotional and cognitive processes as isolated phenomena, the work is structured to reflect how internal states evolve as perceptual, cognitive, and social demands increase.

1.2 Objectives and Structure of the Thesis

The overall aim of this doctoral work is to contribute to a clearer and more systematic understanding of the psychophysiological mechanisms underlying human emotional and cognitive responses across different experimental contexts. Rather than focusing on a single, narrowly defined application, the research is articulated around a set of complementary objectives that collectively support the exploration of how neural and autonomic dynamics complement behavior and subjective experience.

A first objective of this thesis is to investigate the neurophysiological and behavioral correlates of emotional and cognitive processes across controlled yet diverse experimental settings. By examining multiple paradigms, it becomes possible to identify both those mechanisms that appear robust across contexts and those modulations that are specific to particular tasks or stimulus domains. This comparative perspective is intended to highlight potential cross-context markers of psychophysiological organization.

A second objective concerns the adoption and evaluation of advanced analytical methodologies for the study of physiological time series. The emphasis is placed on approaches capable of capturing temporal structure and intrinsic dynamics of the human system from a bioengineering standpoint, including functional connectivity metrics, recurrence-based analysis, and non-linear modeling techniques. These methods are used to complement traditional linear descriptors, with the aim of assessing whether dynamic markers provide additional sensitivity to variations in cognitive or affective states.

A third objective is to pursue a multimodal perspective, integrating neural, autonomic, and behavioral information within coherent analytical frameworks. Since no single physiological modality can fully account for the complexity of internal states, the joint consideration of complementary signals is expected to yield representations that are more robust, interpretable, and transferable across tasks and conditions.

1.2.1 Structure of the Thesis

The doctoral work is supported by an extensive experimental program carried out over three years and organized across six main paradigms that differ in perceptual, cognitive, affective, and social demands. These paradigms required the coordinated acquisition of multimodal physiological data (EEG, EDA, ECG, pupillometry), behavioral indices, facial-expression and voice features, and validated psychological questionnaires. Across all studies, more than 350 participants were recruited, resulting in approximately 290 usable subjects after applying quality-control and modality-specific preprocessing pipelines. This scale allowed both within-context analyses and cross-context comparisons, ensuring that the methodological objectives could be addressed rigorously.

Figure 1.1 provides a synthetic representation of the experimental program. For each paradigm, it reports the physiological signals acquired, the behavioral and psychological instruments used, and the number of participants recruited and included in the analyses. The color coding mirrors the structure of the thesis: studies involving controlled perceptual processing are described in chapter 3 (blue), cognitively engaging tasks in chapter 4 (green), and emotionally or socially enriched paradigms in chapter 5 (orange). As such, the figure serves as a bridge between the scientific objectives of the thesis and its empirical organization.

Following this introductory chapter, the thesis is structured to move pro-

Experimental Task	EEG		EDA		ECG			Pupillometry	FER	Voice	Psychological Tests							no. of Participants	no. Analysed
	DSI-24	SAGA-32	DSI-24 EDA	grove GSR Module Arduino	Shimmer ECG Module	SAGA-32 ECG Module	RUSA Smartex	Tobii Glasses3	WAFER	Shure	SAM	IRI	PAMAS	QCIE	TAS	SPS/SIAS			
Deepfake vs Real Human Face Recognition	✓	□	✓	□	✓	□	□	✓	□	□	□	□	□	□	□	□	45	23	
Words and Pseudowords Aloud Reading	✓	□	✓	□	✓	□	□	□	□	✓	□	□	□	□	□	□	55	45	
Snake and Matching Pairs Videogames	✓	□	□	□	✓	□	✓	□	✓	□	□	□	✓	□	□	□	129	109	
Neuroaesthetics	✓	□	✓	□	□	□	□	□	□	□	✓	✓	□	□	□	□	53	35	
IAPS EDA Modulation in Dyads	□	□	□	✓	□	□	□	□	□	□	✓	□	□	□	□	□	37	32	
IAPS Hyperscanning and Cross-Biofeedback	□	✓	□	□	□	✓	□	□	□	□	✓	□	□	✓	✓	✓	50	50	

Figure 1.1: Summary of the experimental program conducted during the doctoral research.

gressively from theoretical and methodological foundations to the analysis of specific experimental contexts and, ultimately, to broader interpretative considerations. The central organizing principle is the "simple-to-complex" progression introduced earlier. Psychophysiological patterns identified in minimal conditions are used as reference points for interpreting responses in cognitively demanding scenarios and, finally, in affectively or socially enriched environments. This progression supports a unified interpretation of the findings and highlights how neural and autonomic dynamics evolve as contextual demands increase.

The remainder of the thesis is organized as follows:

- chapter 2 introduces the theoretical and methodological framework. It describes the physiological signals considered, preprocessing procedures, linear and nonlinear analytical metrics, and the rationale for employing dynamic and complexity-oriented approaches. The experimental systems and psychological questionnaires used across the different studies are also presented;
- chapter 3 reports two experimental paradigms focused on neural and autonomic responses to simple, highly controlled stimuli differing in familiarity or identifiability. These studies establish a reference map of basic psychophysiological reactivity under constrained laboratory conditions;
- chapter 4 introduces a serious-game oriented paradigm as the second experimental context. Here, psychophysiological measures are examined in relation to task structure, performance, and subjective evaluations. The chapter characterizes how cognitive load, attention, and affective responses interact during active, goal-directed behavior;
- chapter 5 presents three experimental tasks involving emotionally and socially enriched scenarios, such as artworks and affective images in interpersonal or dyadic interactions. These studies investigate how emotional meaning and social presence modulate the neural-autonomic patterns, shifting the focus from individual processing to relational and context-dependent dynamics;
- chapter 6 concludes the thesis by summarizing the main findings across experimental contexts, discussing their implications for multimodal

psychophysiological modeling, and outlining potential applications and directions for future research.

Chapter 2

Theoretical and Methodological Framework

This chapter provides the theoretical and methodological foundations for the acquisition and analysis of the multimodal physiological signals employed throughout the thesis. It introduces the functional organisation of the central and autonomic nervous systems and illustrates how neural activity, cardiovascular dynamics, electrodermal responses, pupillary changes and facial expressions reflect variations in cognitive, emotional and arousal states. Building on these physiological principles, the chapter outlines the main classes of biomedical signals considered, discusses their stochastic and non-stationary nature, and presents the preprocessing and analytical approaches adopted, including both linear and nonlinear methods. The chapter further describes the instrumentation and multimodal experimental setups implemented during the doctoral project, as well as the psychological questionnaires used to complement physiological measures with subjective assessments, thereby establishing the framework that underpins the empirical analyses developed in the subsequent chapters.

This chapter aims to provide the reader with the theoretical and methodological framework for understanding the physiological and technical foundations underlying the acquisition and analysis of the biomedical signals employed in this thesis. The chapter begins by providing the physiological basis of the human nervous system functioning and how its activity may

reflect internal functional states of interest, including emotional activation and inhibition, fluctuations in arousal, cognitive dynamics, as well as baseline or default states. The ability to quantify these states, through sensors' measurements, provides valuable insights into the internal functioning of the human system, particularly in controlled experimental settings aimed at investigating cognitive and emotional processes. Building on these physiological foundations, the chapter introduces the different classes of biomedical signals considered in this work, describing their general properties and the methodological implications arising from their intrinsically variable, stochastic, and non-deterministic nature. For each signal addressed throughout the research activity, the chapter presents the main preprocessing steps and the analytical methodologies employed, encompassing both linear and nonlinear approaches. These methods enable the extraction of metrics and markers that support the characterization of internal states exhibited by participants during the experimental protocols. The chapter then provides a systematic overview of the instrumentation used during the doctoral project, including the experimental setups that were designed, implemented, and deployed for multimodal data acquisition. Finally, it introduces the psychological questionnaires administered across the various studies, which complement the physiological measurements by offering subjective, self-reported assessments from participants.

2.1 Physiological Basis of Human Nervous System

The human nervous system (NS) is conventionally divided into the central nervous system (CNS) and the peripheral nervous system (PNS) [125], as illustrated in Figure 2.1. The CNS, composed of the brain and spinal cord, is responsible for integrating sensory information and generating higher-order processes such as perception, cognition, and emotional regulation. The PNS connects the CNS to the rest of the body through cranial and spinal nerves, and it can be further subdivided into sensory (afferent) pathways, which transmit information from sense organs to the CNS, and motor (efferent) pathways, which convey commands from the CNS to muscles and organs.

Within the motor division of the PNS, two major subsystems can be distinguished. The somatic nervous system governs voluntary actions by controlling skeletal muscles, whereas the autonomic nervous system (ANS)

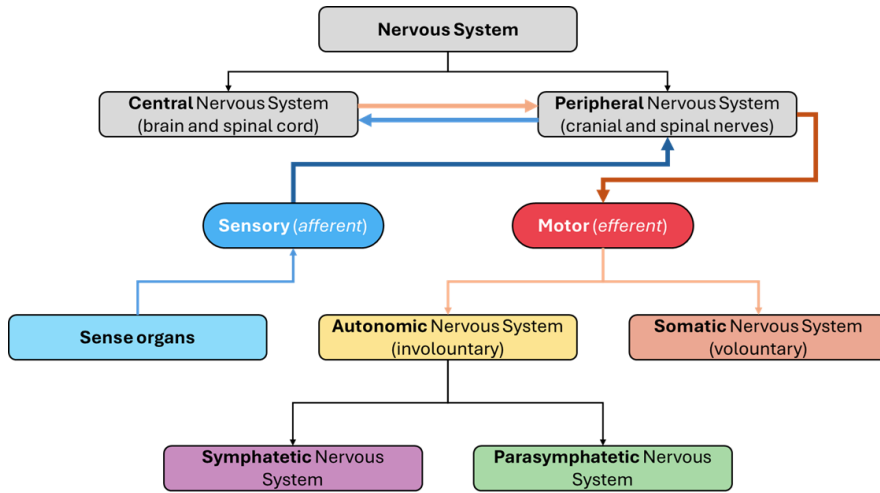


Figure 2.1: Flowchart of the human nervous system.

regulates involuntary physiological functions including heart rate (HR), respiration, digestion, and sweat gland activity. The ANS itself comprises two complementary branches: the sympathetic nervous system (SNS), which supports arousal and "fight-or-flight" responses, and the parasympathetic nervous system (PSNS), which facilitates recovery and "rest-and-digest" processes.

Cognitive tasks and emotional states generally recruit both central neural circuits and autonomic responses. For instance, engaging in a demanding mental task activates specific cortical and subcortical networks in the CNS, while simultaneously modulating autonomic outputs such as cardiac activity, pupil dilation, and EDA responses governed by the SNS. Because of this tight interplay between CNS computations and ANS-driven physiological adjustments, monitoring both neural and peripheral signals offers rich insight into an individual's cognitive workload and emotional arousal [51, 125, 395]. In practice, changes in brain activity and in peripheral markers such as HR, skin conductance, or eye movements serve as objective correlates of mental state under varying cognitive and emotional demands.

These signals can be recorded noninvasively using a wide range of biomedical sensors. However, they exhibit complex properties, including non-linearity, non-stationarity, and substantial inter-individual variability, which require

specialised processing approaches. The following section introduces the main CNS- and ANS-derived signals considered in this work, and discusses their characteristics and utility as markers of cognitive and emotional states.

2.1.1 Physiological Markers of Cognitive and Emotional State

One key measure of CNS activity is EEG, a noninvasive technique that records the brain’s electrical activity via scalp electrodes. EEG reflects the summed postsynaptic potentials from large populations of cortical pyramidal neurons [272], producing oscillatory patterns that map reliably onto distinct functional states. A large body of evidence shows that EEG spectral power is sensitive to cognitive workload: alpha rhythms typically dominate during relaxed wakefulness, whereas increased theta and beta activity emerge with higher cognitive demands, sustained attention, and complex mental processing [272]. Moreover, frontal theta power increases with rising mental effort, while parietal alpha often decreases as task demands grow, revealing the redistribution of neural resources under load. These effects can be quantified to demonstrate robust associations between workload and theta, alpha, and beta power changes [85]. Event-related potentials and time-frequency indices further allow tracking instantaneous fluctuations in cognitive engagement and processing efficiency [125]. Beyond workload, EEG is also informative about emotional processing, as oscillatory activity, particularly in frontal regions, varies systematically with affective state and arousal [409]. This makes EEG a versatile tool for capturing both cognitive and emotional dynamics. Thanks to its millisecond-level temporal resolution and compatibility with mobile or wearable systems, EEG provides a direct, continuous window into central neural activity during tasks involving attention, working memory, decision-making, or affective engagement [15].

Complementing the CNS measures, peripheral signals originated from the cardiovascular and sweat gland systems reflect the involuntary stress and arousal responses of the body. HRV, the beat-to-beat variation in HR, is a sensitive indicator of ANS balance; higher HRV generally signifies robust parasympathetic (calming) influence, whereas stress or mental effort often leads to reduced HRV due to increased sympathetic activity. EDA (also known as galvanic skin response, GSR) measures the skin’s electrical conductance, which rises with sweat gland activity. Since sweat glands are controlled exclusively by the SNS, EDA is a direct proxy of sympathetic

arousal [395]. Both HRV and EDA have been established as reliable measures of autonomic nervous system activation and are widely used to assess psychophysiological stress levels [51, 395]. For instance, a cognitively demanding or emotionally stressful task can simultaneously trigger an increase in the EDA skin conductance responses and a shift in HRV power toward the higher-frequency (sympathetic) component [51]. By tracking these changes, researchers can infer the presence of mental stress or emotional excitement. Notably, using EDA and HRV in combination enhances the ability to detect cognitive workload, since they capture complementary facets of autonomic response to mental challenges [51].

In addition to brain and peripheral physiological signals, ocular-derived metrics offer a valuable non-invasive window into cognitive and emotional processing. Pupillometry, the measurement of pupil diameter, takes advantage of the fact that the pupil is jointly influenced by sensory input and internal cognitive states. Beyond the well-known light-evoked constriction, the pupil reliably dilates when mental effort, arousal, or attentional demands increase [402, 411]. This dilation is closely linked to activity in brainstem arousal systems, particularly the locus coeruleus, which modulates autonomic balance and adjusts pupil size in relation to task engagement and cognitive load [48, 372]. As a result, pupil diameter provides a sensitive and unobtrusive marker of the interaction between central cognitive processes and autonomic activation. Modern eye-tracking systems can capture these fluctuations with high temporal precision, making pupillometry a widely used indicator of cognitive workload and emotional arousal [363].

Finally, facial expressions serve as an outward behavioral signal of internal emotional and cognitive states. Human emotions are not purely internal, as they are often expressed spontaneously via facial muscle movements [331]. A person's facial expression (FE) thus conveys their emotional state and is a key modality of non-verbal communication [331]. For example, emotions like fear or joy manifest in characteristic facial patterns (e.g. widened eyes, furrowed brows, smiles), which can be detected and quantified using computer vision techniques. FE analysis, or facial emotion recognition (FER), can complement physiological sensors by providing a direct measure of observable affective responses. Importantly, these expressions are driven by activity in the central nervous system's emotion circuits and accompanied by physiological changes in the body [395].

Each modality offers a different "window" into how the human body and

brain respond to cognitive demands or emotional stimuli. The following sections will build on this physiological foundation by detailing the specific instrumentation and analysis methods used to capture these signals, and by explaining how their unique signal properties can be handled to extract meaningful features. These methodological considerations are crucial because biomedical signals possess distinctive characteristics (such as noise, variability, and non-linear dynamics) that must be addressed to reliably interpret the physiological responses captured throughout the experimental tasks.

2.2 Characteristics of Biomedical Signals

Biomedical signals are physical manifestations of physiological activity that convey information about one or more biological subsystems involved in the observed process [75]. These signals can be generated and recorded at multiple spatial and functional scales, ranging from cellular electrophysiological activity to organ-level functions such as cardiac or cerebral dynamics, and even to population-level physiological patterns. The essential purpose of biomedical signal processing is to enhance and extract this embedded information in a way that is optimally suited to the experimental objectives and the biological question under investigation. Accordingly, there is no universal method of signal analysis; rather, distinct approaches must be selected depending on the system's characteristics, the available *a priori* knowledge, and the trade-off between interpretability and computational complexity.

From a general perspective, biomedical signals possess several properties that distinguish them from signals encountered in physics or engineering [75, 357]:

1. They originate from dynamical systems with diverse and often nonlinear behaviors;
2. They usually result from the interaction among biological subsystems (e.g., neural-autonomic coupling);
3. They exhibit high variability, both intra- and inter-individual, reflecting adaptive regulation and biological diversity;
4. They are frequently corrupted by noise with mixed endogenous and exogenous origins.

Even such "noise" may carry physiological meaning, since endogenous fluctuations often reveal intrinsic variability rather than measurement error. These features make biomedical signals intrinsically complex, context-dependent, and non-repeatable under identical conditions, posing both conceptual and methodological challenges for analysis.

Biomedical signals therefore cannot be adequately represented as stationary, purely deterministic time series; instead, they should be treated as stochastic processes whose dynamics evolve over time. Formally, a biomedical signal can be expressed as a stochastic process $x(t, \omega)$ (see Equation 2.1), where t denotes time and ω represents the outcome in the underlying probability space Ω :

$$x(t, \omega) \in \mathbb{R}, \quad \forall t \in \mathbb{R}^+, \omega \in \Omega. \quad (2.1)$$

In this formulation, the signal observed at time t is a realization of a random variable, and the ensemble of realizations forms the probabilistic structure of the process. Because the mechanisms generating these signals involve both deterministic physiological processes (e.g., pacemaker oscillations, cortical activity) and random perturbations (e.g., neural noise, physiological and non-physiological artifacts), their behavior is best described as stochastic-deterministic. A simplified representation is shown in Equation 2.2:

$$x(t) = s(t) + n(t), \quad (2.2)$$

where $s(t)$ denotes the underlying deterministic component and $n(t)$ the stochastic fluctuations. In many cases, the boundary between these components is conceptual rather than separable, as both may contain physiologically meaningful information [169].

2.2.1 Deterministic and stochastic characteristics

A system is said to be deterministic when its future evolution can be fully predicted from its past behavior. A signal generated by such a system is deterministic if, at each instant t_k , its value $y(t_k)$ can be computed through a closed mathematical expression or inferred from a finite number of preceding samples. Consequently, the parameters of a deterministic signal can be directly obtained from its analytical expression or from its graphical representation [75]. Conversely, a stochastic system cannot be predicted through deterministic equations. A stochastic signal must therefore be analyzed using statistical methods. Formally, each sample $y(t_k)$ is treated as a random variable with an associated probability distribution $p(y(t_k))$, and the observed

signal is considered one particular realization of the underlying stochastic process [75].

Purely deterministic or purely stochastic biological signals do not exist; rather, they vary along a continuum. The ECG, for example (Figure 2.2, top), can be considered quasi-deterministic, since its waveform morphology allows short-term prediction and direct measurement of parameters such as amplitudes or intervals. Nonetheless, beat-to-beat variability and noise introduce unpredictable elements. Conversely, the EEG is predominantly stochastic (Figure 2.2, middle), reflecting the asynchronous summation of cortical neuronal populations. Yet even within EEG, locally deterministic patterns can emerge, for instance in oscillatory bursts or evoked responses recorded from specific cortical areas (Figure 2.2, bottom). Transient biological signals, such as action potentials or event-related potentials (ERPs), constitute a distinct class: their occurrence is temporally locked to external or internal events and their influence decays within finite time intervals. These distinctions are not merely conceptual, they determine the appropriate mathematical and statistical tools to be applied, from parametric modeling for deterministic trends to probabilistic and spectral methods for stochastic dynamics.

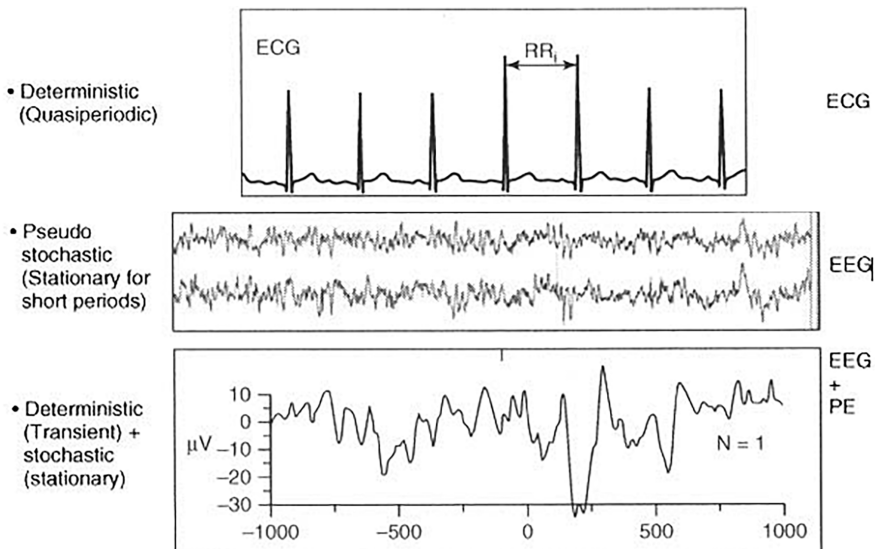


Figure 2.2: A few biomedical signals and their statistical characteristics. [75]

2.2.2 Stationarity, variability, and complexity

A defining feature of biomedical signals is their nonstationarity. The statistical characteristics of $x(t)$, such as mean and variance, change over time due to physiological adaptation, behavioral context, and environmental conditions. Mathematically, this means that the joint probability distribution depends on the absolute time indices (Equation 2.3):

$$P(x_{t_1}, x_{t_2}, \dots, x_{t_n}) \neq P(x_{t_1+\tau}, x_{t_2+\tau}, \dots, x_{t_n+\tau}) \quad (2.3)$$

for arbitrary time shifts τ . Such nonstationarity motivates the use of time-frequency and adaptive approaches, including short-time Fourier and wavelet transforms, to capture transient features [357].

Biological signals also exhibit remarkable variability and complexity. Variability represents spontaneous fluctuations around physiological set-points, while complexity refers to the organized, scale-dependent structure of these fluctuations [170]. Healthy physiological systems display intricate dynamics, neither periodic nor random, characterized by long-range correlations, fractal behavior, and non-Gaussian statistics. The loss of such "organized variability" is often associated with pathological or dysfunctional states.

2.2.3 From linear to nonlinear and dynamical analysis

Classical linear techniques, such as spectral and correlation analyses, assume superposition and proportionality between input and output, assumptions that rarely hold in feedback-dominated biological systems. While linear models (e.g., autoregressive models) remain useful for local approximations, they cannot capture the nonlinear dependencies and emergent dynamics typical of physiological regulation [75, 217].

Nonlinear dynamics provides a theoretical framework in which biological systems are viewed as deterministic yet unpredictable, exhibiting sensitive dependence on initial conditions. Given a time series $x(t)$, the underlying state space can be reconstructed through delay embedding [416] as reported in Equation 2.4:

$$\mathbf{x}(t) = [x(t), x(t - \tau), x(t - 2\tau), \dots, x(t - (m - 1)\tau)], \quad (2.4)$$

where m is the embedding dimension and τ the delay. This reconstruction enables geometrical analyses of attractors, trajectories, and recurrence

patterns. In physiological data, nonlinear metrics such as correlation dimension, Lyapunov exponents, and entropy-based measures (e.g., approximate entropy, sample entropy, multiscale entropy) quantify the degree of order, predictability, and information content [95, 349, 360]. These descriptors reveal subtle temporal signatures associated with cognitive effort, emotional arousal, or disease-related alterations in autonomic control.

2.2.4 Methodological implications and acquisition chain

Recognizing the stochastic, nonlinear, and adaptive nature of biomedical signals has deep methodological implications. Analytical frameworks must accommodate:

1. the coexistence of deterministic and random components within physiological variability;
2. the nonstationarity and context dependence of biological processes;
3. the importance of time-frequency and scale-dependent representations;
4. the necessity of nonlinear and multivariate tools for system-level characterization.

From an engineering perspective, biomedical signal analysis follows a canonical processing chain: acquisition through sensors or transducers, amplification and analog conditioning, antialiasing filtering, analog-to-digital conversion and quantization, followed by preprocessing and feature extraction. Each stage can introduce distortions affecting the statistical and dynamical properties of the data, particularly critical for nonlinear metrics sensitive to amplitude scaling and temporal resolution. Awareness of this acquisition-processing interplay ensures that subsequent analyses faithfully reflect genuine physiological dynamics rather than methodological artifacts.

In this view, physiological variability is not noise to be suppressed but information to be decoded, a reflection of the underlying self-organizing dynamics of the human organism. This theoretical framework poses the basis for all subsequent analyses performed within this thesis, forming the conceptual bridge between biological systems and their mathematical representations.

2.3 Electroencephalography (EEG)

The EEG reflects the macroscopic electrical activity generated by the cerebral cortex. Physiologically, EEG signals originate mainly from excitatory and inhibitory postsynaptic potentials produced in the dendrites and somata of cortical pyramidal neurons, which are arranged in parallel and oriented perpendicular to the cortical surface. This architecture allows their extracellular potentials to summate and propagate through the cerebrospinal fluid, skull, and scalp. These cortical potentials arise from ongoing physiological control processes, cognitive operations, and responses to external sensory stimuli, which modulate synaptic input across distributed cortical networks. The EEG measured at the scalp represents an average of the heterogeneous activity of many small cortical zones underlying each electrode, rather than the brief action potentials of individual neurons. Different EEG frequency bands correspond to distinct physiological states. Delta and theta activity emerges during sleep or pathological slowing, alpha rhythms characterize relaxed wakefulness with eyes closed, while beta and gamma activity reflect alertness, sensory processing, attention, and cognitive engagement. Scalp EEG is typically recorded using multiple surface electrodes placed over standardized positions according to the International 10-20 system. Electrodes are arranged at fixed percentages of the nasion-inion and left-right preauricular distances, ensuring symmetrical and reproducible spatial sampling of cortical activity.

2.3.1 EEG Preprocessing: The HAPPE Workflow

In the different experimental studies conducted in this doctoral work, except for the work presented in section 5.3, EEG signals were preprocessed following the Harvard Automated Processing Pipeline for EEG (HAPPE), a standardized and fully automated pipeline designed to handle high-artifact recordings [163, 164]. Given the known sensitivity of several EEG-derived metrics to preprocessing choices, the adoption of a standardized and automated pipeline also served to minimise operator-dependent variability and to improve reproducibility across the different experimental paradigms analysed in this dissertation. Following the HAPPE workflow (Figure 2.3), initially EEG data were band-pass filtered using experiment-specific ranges. The lower edge was consistently set to 1 Hz to remove slow drifts and very low-frequency artifacts, and to constrain the subsequent independent compo-

ment analysis (ICA) decomposition to a stable frequency range. The upper edge differed across experiments depending on the recording device and the spectral characteristics of interest. In particular, high-frequency components above 45 Hz or above 80 Hz were removed when they contained little physiological information relative to the study aims and might be influenced by muscle artefacts, environmental noise, or device-specific high-frequency limitations.

The general form of a filtering process is defined as in Equation 2.5:

$$x_{\text{filtered}}(t) = x(t) * h(t), \quad (2.5)$$

where $h(t)$ denotes the impulse response of the selected filter.

Line noise (50 Hz) was removed using multitaper regression, by estimating and subtracting sinusoidal components. HAPPE adopts CleanLine's [322] multi-taper regression to remove line noise without distorting nearby EEG frequencies, avoiding the drawbacks of notch filters. CleanLine automatically scans around the target frequency (± 2 Hz) and applies regression using 4-second windows, 1-second steps, a smoothing tau of 100, and a significance threshold of $p = 0.01$. Any residual line noise is further reduced through subsequent wavelet-thresholding, ICA, and re-referencing steps.

Bad channels were then identified using the joint-probability criterion. Specifically, a channel was marked as artifactual if its log-power distribution deviated more than three standard deviations from the mean or if correlated more than 80% with other channels. Detected bad channels were excluded from ICA and later reconstructed through spherical spline interpolation.

Then, a wavelet-thresholding ICA (W-ICA) was applied before standard ICA decomposition to account for substantial artifact contamination or noisy recordings. The wavelet threshold is computed as in Equation 2.6:

$$\text{Threshold} = \frac{\text{median}(|D|)}{0.6745} \sqrt{2 \log(N)}. \quad (2.6)$$

where D represents the detail coefficients of the wavelet decomposition and N the signal length. Artifact removal was then completed by means of the ICA, followed by automated component classification using the triple Artifact Rejection Algorithm (MARA) [453]. Components with artifact probability greater than 0.5 were rejected. This step allows to remove ocular, muscular, cardiac, and non-stereotyped artifacts.

For ERP analyses, the EEG was segmented around the events of interest. Epochs were rejected based on amplitude and joint-probability thresholds, typically using a $\pm 40 \mu V$ criterion.

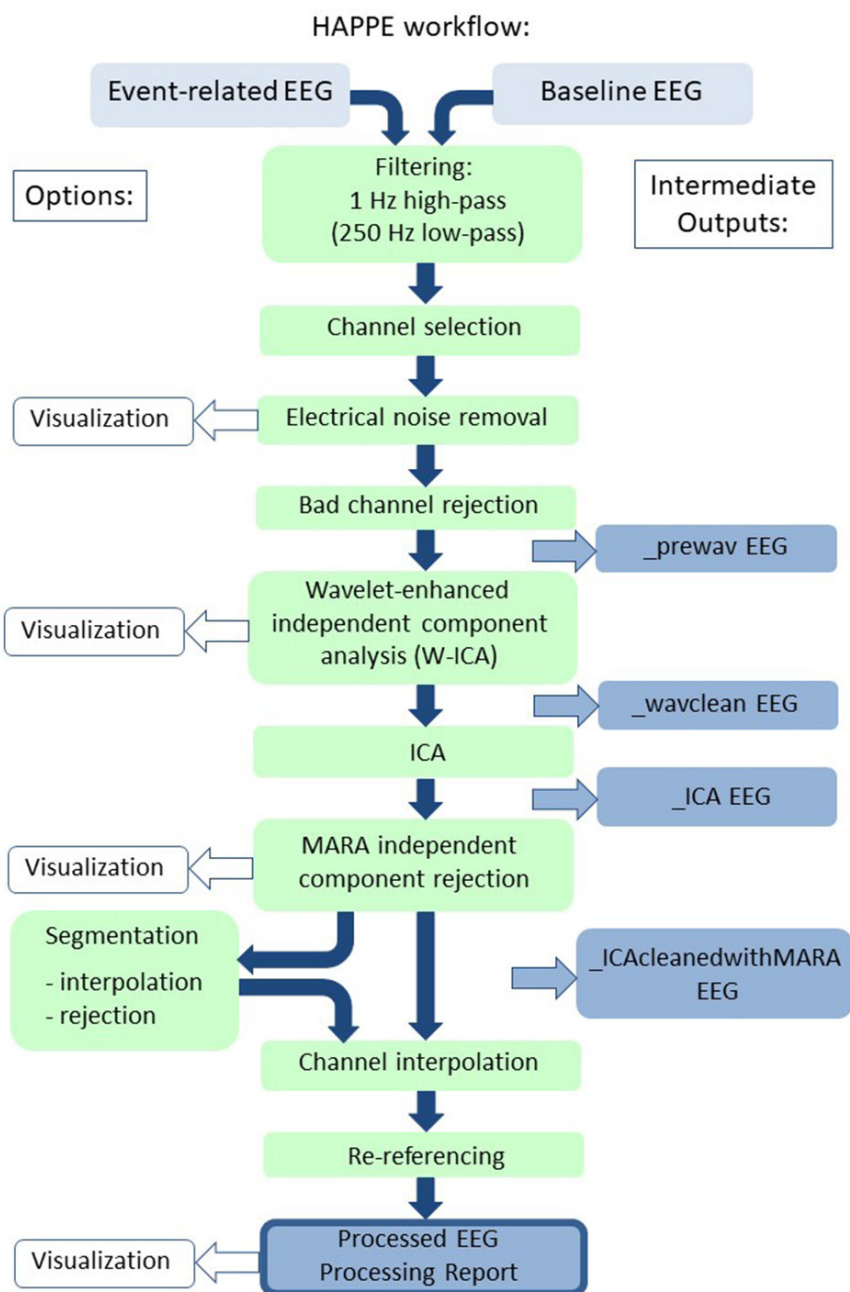


Figure 2.3: Schematic illustrating the HAPPE pipeline's processing steps. [164]

Bad channels identified during preprocessing were then reconstructed through spherical spline interpolation. Finally, re-referencing was performed. The unipolar common average reference (CAR) was applied consistently within each EEG study.

2.3.2 ERP Analysis

In the studies reported in section 3.1 and section 3.2, ERPs were computed by averaging time-locked epochs. Averaging was performed across spatially contiguous groups of electrodes (regions of interest, ROIs) corresponding to specific cortical areas. For a set of extracted epochs $x_i(t)$, the ERP waveform of the ROI r is defined in Equation 2.7:

$$\text{ERP}(t) = \frac{1}{N} \sum_{i=1}^N x_i(t), \quad (2.7)$$

where N is the number of accepted trials.

ERP components were characterized through latency and amplitude measures using area-based metrics to increase robustness against physiological noise and avoid reliance on single-sample peak values.

Fractional Area Latency Latency was computed using the fractional area method [277], defined as the time point at which a fixed proportion of the total area under the ERP curve within a predefined component window $[t_1, t_2]$ is reached. For a fraction $\alpha = 0.5$, i.e., 50%), the fractional area latency t_{lat} is defined in Equation 2.8:

$$\int_{t_1}^{t_{\text{lat}}} \text{ERP}(t) dt = \alpha \int_{t_1}^{t_2} \text{ERP}(t) dt. \quad (2.8)$$

Thus, t_{lat} is the earliest time point such that the accumulated area equals α times the total component area. In the studies considered here, the latency of each component was computed as the time at which 50% of the total area within the considered ERPs window was reached.

Area-Based Amplitude Measure To reduce sensitivity to transient fluctuations and single-point noise, amplitude was estimated using the total area of the ERP waveform within the component window rather than its maximum peak value. The area-based amplitude A_{area} is defined in Equation 2.9:

$$A_{\text{area}} = \int_{t_1}^{t_2} \text{ERP}(t) dt. \quad (2.9)$$

This metric provides a more stable estimate of component magnitude, capturing the overall deflection rather than its instantaneous peak.

2.3.3 Spectral Power Analysis

For a discrete signal $x[n]$ sampled at f_s , the Power Spectral Density (PSD) estimate is given by Equation 2.10:

$$P_{xx}(f) = \frac{1}{K} \sum_{k=1}^K \left| \frac{1}{N_w} \sum_{n=0}^{N_w-1} x_k[n] w[n] e^{-j2\pi f n / f_s} \right|^2. \quad (2.10)$$

The spectral power can be expressed in logarithmic units, as reported in Equation 2.11:

$$\text{PSD}_{\text{dB}}(f) = 10 \log_{10}(P_{xx}(f)). \quad (2.11)$$

Band-specific power was quantified by averaging the PSD over the set F of discrete frequency bins belonging to each canonical band. In linear units, this corresponds to Equation 2.12:

$$P_{\text{band}} = \frac{1}{|F|} \sum_{f \in F} P_{xx}(f), \quad (2.12)$$

while in logarithmic unit, Equation 2.13 applies:

$$P_{\text{band}}^{\text{dB}} = \frac{1}{|F|} \sum_{f \in F} \text{PSD}_{\text{dB}}(f). \quad (2.13)$$

The canonical EEG frequency bands considered in this thesis were:

- **Delta:** 1–4 Hz (section 3.1, section 4.2)
- **Theta:** 4–7 Hz (section 3.1, section 4.2) or 4–8 Hz (section 5.1)
- **Alpha:** 8–12 Hz (section 3.1) or 8–13 Hz (section 4.2 and section 5.1)
- **Beta:** 13–25 Hz (section 4.2), 13–30 Hz (section 5.1), or 13–32 Hz, subdivided into:

- Low Beta: 13–17 Hz (section 3.1 and section 3.2)
- High Beta: 18–32 Hz (section 3.1 and section 3.2)
- **Gamma:** 25–45 Hz (section 4.2) or 32–48 Hz (section 3.1 and section 3.2) or 30–80 Hz (section 5.1)

2.3.4 Functional Connectivity: Phase Lag Index (PLI)

In the study presented in section 5.1, functional connectivity was quantified using the Phase Lag Index (PLI), a measure designed to minimize the influence of volume conduction and common reference effects by selectively capturing non-zero phase relationships between EEG channels [400,441]. Instantaneous phase was extracted by applying the Hilbert transform to the band-limited analytic signal. For a time series $x(t)$, the instantaneous phase is defined in Equation 2.14:

$$\phi(t) = \arctan \left(\frac{\mathcal{H}[x(t)]}{x(t)} \right), \quad (2.14)$$

where $\mathcal{H}[\cdot]$ denotes the Hilbert transform. The instantaneous phase difference between two channels x and y is shown in Equation 2.15:

$$\Delta\phi(t) = \phi_x(t) - \phi_y(t). \quad (2.15)$$

PLI quantifies the consistency of the sign of these phase differences over time, as defined in Equation 2.16:

$$\text{PLI} = |\langle \text{sign}[\sin(\Delta\phi(t))] \rangle|, \quad (2.16)$$

where $\langle \cdot \rangle$ denotes temporal averaging. PLI values close to 0 indicate the absence of consistent phase coupling, whereas values approaching 1 reflect a stable non-zero phase lag that is unlikely to arise from instantaneous field spread [400].

In line with recommendations for event-related connectivity analyses [38, 91, 243], PLI was computed over short EEG windows, as the choice of longer windows may inflate connectivity estimates by averaging across periods characterized by attentional drift, blinks, and diverse stages of processing. In section 5.1, connectivity matrices were computed separately for different bands and each adjacency matrix was subjected to proportional thresholding.

Graph-theoretical features were extracted using the Brain Connectivity Toolbox (BCT) [366], including mean strength, clustering coefficient, transitivity, global and local efficiency, participation coefficient, betweenness centrality, modularity Q , and characteristic path length λ . For completeness, below are summarized the formulations used for weighted, undirected networks derived from the PLI connectivity matrices after proportional thresholding.

Let $W = [w_{ij}]$ be the weighted adjacency matrix, with $w_{ij} = w_{ji} \geq 0$ and $w_{ii} = 0$. The weighted strength of node i is given by (Equation 2.17):

$$s_i = \sum_{j=1}^N w_{ij}. \quad (2.17)$$

Mean strength The mean strength of the network is the average of node strengths (Equation 2.18):

$$\langle s \rangle = \frac{1}{N} \sum_{i=1}^N s_i. \quad (2.18)$$

Clustering coefficient For a weighted, undirected graph, the local clustering coefficient of node i is (Equation 2.19):

$$C_i = \frac{1}{k_i(k_i - 1)} \sum_{\substack{j,k=1 \\ j \neq k}}^N (w_{ij} w_{ik} w_{jk})^{1/3}, \quad (2.19)$$

for $k_i \geq 2$, and $C_i = 0$ otherwise. The global clustering coefficient is (Equation 2.20):

$$C = \frac{1}{N} \sum_{i=1}^N C_i. \quad (2.20)$$

Transitivity Transitivity quantifies the overall prevalence of triangles in the network. For weighted, undirected graphs it can be expressed as (Equation 2.21):

$$T = \frac{\sum_{i=1}^N \sum_{\substack{j,k=1 \\ j \neq k}}^N (w_{ij} w_{ik} w_{jk})^{1/3}}{\sum_{i=1}^N k_i(k_i - 1)}. \quad (2.21)$$

Characteristic path length Shortest path lengths are computed on the weighted graph by defining edge lengths as the inverse of weights (Equation 2.22),

$$\ell_{ij} = \frac{1}{w_{ij}} \quad \text{for } w_{ij} > 0, \quad (2.22)$$

and then obtaining d_{ij} as the minimal sum of edge lengths along any path connecting i and j . The characteristic path length is (Equation 2.23):

$$L = \frac{1}{N(N-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^N d_{ij}. \quad (2.23)$$

Global efficiency Global efficiency is defined as the average inverse shortest path length (Equation 2.24):

$$E_{\text{glob}} = \frac{1}{N(N-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^N \frac{1}{d_{ij}}. \quad (2.24)$$

Betweenness centrality Let σ_{st} be the number of shortest paths between nodes s and t , and $\sigma_{st}(i)$ the number of such paths that pass through node i . The weighted betweenness centrality of node i is (Equation 2.25):

$$BC_i = \sum_{\substack{s,t=1 \\ s \neq t \\ s \neq i \\ t \neq i}}^N \frac{\sigma_{st}(i)}{\sigma_{st}}. \quad (2.25)$$

To obtain a network-level descriptor, betweenness centrality is averaged across all nodes (Equation 2.26):

$$\langle BC \rangle = \frac{1}{N} \sum_{i=1}^N BC_i. \quad (2.26)$$

Participation coefficient Assume that the network is partitioned into M non-overlapping modules, and let $s_{i,m}$ denote the strength of node i to nodes within module m . The participation coefficient of node i is (Equation 2.27)

$$P_i = 1 - \sum_{m=1}^M \left(\frac{s_{i,m}}{s_i} \right)^2, \quad (2.27)$$

with $P_i = 0$ if $s_i = 0$. The network-level participation coefficient is the average across all nodes (Equation 2.28):

$$\langle P \rangle = \frac{1}{N} \sum_{i=1}^N P_i. \quad (2.28)$$

Modularity Q Let c_i be the community assignment of node i . For a weighted, undirected graph, modularity is defined as (Equation 2.29 and Equation 2.30):

$$Q = \frac{1}{2w_{\text{tot}}} \sum_{i=1}^N \sum_{j=1}^N \left(w_{ij} - \frac{s_i s_j}{2w_{\text{tot}}} \right) \delta(c_i, c_j), \quad (2.29)$$

where

$$w_{\text{tot}} = \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N w_{ij} \quad (2.30)$$

is the total weight of the network, and $\delta(c_i, c_j)$ is the Kronecker delta, equal to 1 if $c_i = c_j$ and 0 otherwise.

2.3.5 Hyperscanning: Frontal Alpha Asymmetry, Laterality Quotient and Phase Locking Value

In the cross-biofeedback and hyperscanning study aimed at investigating interpersonal synchronisation during a visual affective task in dyads (presented in section 5.3), the real-time biofeedback presentation required selecting a metric that could reflect participants' subjective perceptions and emotional states. Frontal Alpha Asymmetry (FAA) was chosen as the neurofeedback index of the emotional responses [90]. FAA represents the relative difference in the activity of the alpha band (8–13 Hz) between the left and right frontal hemispheres. According to Metzen et al. (2022) [306], individual EEG alpha asymmetry can be quantified using a Laterality Quotient (LQ), computed as the difference between the natural logarithm of right and left alpha power (Equation 2.31):

$$LQ = \ln(P_{\text{right}}) - \ln(P_{\text{left}}) \quad (2.31)$$

Positive LQ values indicate higher relative right alpha power (i.e., higher left cortical activity), while negative LQ values indicate the opposite.

Moreover, the analysis of synchronisation was achieved through the Phase Locking Value (PLV), which was selected as a measure of phase synchrony and represents an indicator of neural coupling. Within a defined time window, the phase difference between pairs of EEG electrodes is calculated [32].

Given multiple windows of EEG signals from two channels, the PLV is defined as follows (Equation 2.32):

$$PLV(t) = \frac{1}{N} \left| \sum_{n=1}^N e^{i\theta(t,n)} \right| \quad (2.32)$$

Where N is the number of windows and $\theta(t,n)$ represents the instantaneous phase difference between the two signals at time t and window n [22].

2.4 Electrodermal Activity (EDA)

The EDA is a psychophysiological signal reflecting fluctuations in the electrical activity of the skin, which are tightly linked to psychological processes and sympathetic nervous system activity. These variations, commonly captured through the Skin Conductance Response (SCR), originate primarily from sweat secretion by eccrine sweat glands, particularly dense in regions such as the palms and soles. Because sweat consists largely of water and electrolytes, its presence modulates skin conductance and related electrical properties, enabling reliable measurement through electrodes placed on the fingers or wrist. Although the primary function of eccrine glands is thermoregulation, they also respond to psychologically salient events including emotional arousal, stress, and cognitive load. This modulation is driven exclusively by sympathetic innervation, as these glands lack parasympathetic input. Consequently, EDA represents a specific and sensitive index of sympathetic nervous system activity, providing a robust marker of autonomic reactivity to external stimuli [431].

EDA is typically decomposed into two components: a tonic component, representing slow fluctuations in baseline conductance associated with general arousal, and a phasic component, consisting of rapid SCR peaks elicited by discrete stimuli. This decomposition allows for a more precise characterization of psychophysiological responses by distinguishing immediate sympathetic activation from slower background variations. Due to this specificity, EDA is widely used to assess stress and anxiety, often proving more sensitive

than other physiological measures such as HR, respiration, or skin temperature. Previous studies have shown that increases in SCR amplitude, elevations in tonic levels (SCL), and higher frequencies of non specific responses reliably indicate heightened reactivity in stressful contexts [431].

Over time, EDA has found broad application across multiple research domains [153], becoming a widely adopted tool for investigating psychological disorders and cognitive or emotional processes. Notable applications include research on mood disorders and depression [374], autism spectrum condition [351], anxiety disorders [379], as well as studies examining responses to sensory, for example olfactory [344], or cognitive stimuli.

2.4.1 EDA Analysis

In the studies reported in section 3.2 and section 5.2, EDA was used as a peripheral marker of sympathetic nervous system activation. Although acquisition setups and task structures varied across experiments, the analysis of EDA followed a common framework, centered on a standardized preprocessing and decomposition of the skin conductance (SC) signal into tonic and phasic components using the *cvxEDA* algorithm [176], and on the extraction of complementary sets of features, ranging from time and frequency domain indices [29] to nonlinear complexity measures such as sample entropy features and *ComEDA* [323].

2.4.2 EDA Decomposition: the *cvxEDA* Algorithm

The EDA signal decomposition was performed using the convex optimization based *cvxEDA* algorithm [87, 176], which is widely adopted in the literature for separating tonic and phasic components of the SC signal. The adoption of this algorithm provides a principled and reproducible framework for EDA analysis, reducing operator dependent variability and allowing consistent estimation of sympathetic activity across the different experimental paradigms. EDA signals were recorded using wearable sensors with sampling frequencies of 50 Hz (section 5.2) and 300 Hz (section 3.2). Before performing the *cvxEDA* decomposition, the SC signal was first z-score normalized to facilitate algorithm convergence [29].

Following [176], the observed SC time series $\mathbf{y} \in \mathbb{R}^N$ can be modeled as the sum of a phasic component $\mathbf{r}$, a tonic component $\mathbf{t}$, and an additive noise

term ε (Equation 2.33):

$$\mathbf{y} = \mathbf{r} + \mathbf{t} + \varepsilon, \quad (2.33)$$

where ε is assumed to be an independent and identically distributed Gaussian noise process with zero mean and variance σ^2 (Equation 2.34):

$$\varepsilon_i \sim \mathcal{N}(0, \sigma^2). \quad (2.34)$$

Tonic Component The tonic component $\mathbf{t}$ represents the slow baseline SCL and its spontaneous fluctuations. In Greco et al. it is modeled as a linear combination of cubic B-spline basis functions plus a linear trend [176] (Equation 2.35):

$$\mathbf{t} = B\boldsymbol{\alpha} + C\mathbf{d}, \quad (2.35)$$

where:

- B is an $N \times Q$ matrix whose columns are cubic B-spline basis functions with knots typically spaced every 10 s,
- $\boldsymbol{\alpha} \in \mathbb{R}^Q$ is the vector of spline coefficients,
- C is an $N \times 2$ matrix with $C_{i,1} = 1$ and $C_{i,2} = i/N$, modeling offset and linear trend,
- $\mathbf{d} \in \mathbb{R}^2$ contains the intercept and slope parameters of the tonic drift.

Phasic Component and Sudomotor Nerve Activity The phasic component $\mathbf{r}$ captures SCRs, fast changes in SC driven by discrete bursts in the sudomotor nerve activity (SMNA). Under the assumption of a linear time invariant peripheral system, each phasic response is modeled as the convolution between a sparse, non negative SMNA driver $\mathbf{p}$ and a subject specific impulse response function (IRF) $h(\tau)$ [176]. The IRF is chosen as a bi exponential Bateman function (Equation 2.36):

$$h(\tau) = \left(e^{-\tau/\tau_0} - e^{-\tau/\tau_1} \right) u(\tau), \quad (2.36)$$

where τ_0 and τ_1 are the slow and fast time constants, and $u(\tau)$ is the unit step function.

In discrete time, this dynamics can be represented by an autoregressive moving average (ARMA) system, whose transfer function $H(z)$ can be written as in Equation 2.37 and Equation 2.38:

$$H(z) = \frac{(1 + z^{-1})^2}{\psi + \theta z^{-1} + \zeta z^{-2}}, \quad (2.37)$$

with

$$\psi = \frac{(\tau_1^{-1}\delta + 2)(\tau_0^{-1}\delta + 2)}{(\tau_1^{-1}\delta^2 - \tau_0^{-1}\delta^2)}, \quad \theta = \frac{2\tau_1^{-1}\tau_0^{-1}\delta^2 - 8}{(\tau_1^{-1}\delta^2 - \tau_0^{-1}\delta^2)}, \quad \zeta = \frac{(\tau_1^{-1}\delta - 2)(\tau_0^{-1}\delta - 2)}{(\tau_1^{-1}\delta^2 - \tau_0^{-1}\delta^2)}, \quad (2.38)$$

where δ is the sampling interval.

In matrix form, the phasic response can be written as (Equation 2.39):

$$\mathbf{q} = A^{-1}\mathbf{p}, \quad \mathbf{r} = M\mathbf{q}, \quad (2.39)$$

where A and M are tridiagonal matrices defined by the ARMA coefficients, $\mathbf{p}$ represents the SMNA driver, and $\mathbf{q}$ is an auxiliary variable used to obtain $\mathbf{r}$.

Bayesian and Convex Optimization Framework The unknown parameters $(\mathbf{q}, \boldsymbol{\alpha}, \mathbf{d})$ and the derived quantities $(\mathbf{t}, \mathbf{r}, \mathbf{p})$ are estimated within a Bayesian maximum a posteriori (MAP) framework. Priors enforce physiologically sound constraints [176]:

- SMNA $\mathbf{p}$ is sparse and non negative, modeled through an exponential prior derived from a Poisson description of spike trains;
- spline coefficients $\boldsymbol{\alpha}$ follow a Gaussian prior promoting smoothness of the tonic component;
- the drift parameters $\mathbf{d}$ are given weak or uninformative priors.

Under these assumptions, the MAP problem can be formulated as a convex quadratic optimization, where the cost function includes a data fitting term and regularization terms that enforce sparsity on $\mathbf{p}$ and smoothness on $\boldsymbol{\alpha}$, subject to non negativity constraints on the SMNA ($\mathbf{p} \geq 0$). The solution provides three signals for each recording: the denoised SC signal, its SCL (tonic) component, its SCR (phasic) component, and the underlying SMNA driver.

2.4.3 EDA Features

Following the cvxEDA decomposition, several features were extracted to quantify tonic and phasic sympathetic activity in the studies reported in section 3.2 and section 5.2, following the approaches described in [29] and [323].

Let $SCL(n)$ denote the tonic component and $SCR(n)$ the phasic component or a derived non specific SCR (NSSCR) sequence, defined over a window of N samples.

Tonic Activity Features The mean and variability of the SCL provide global indices of tonic arousal (Equation 2.40 and Equation 2.41):

$$SCL_{\text{mean}} = \frac{1}{N} \sum_{n=1}^N SCL(n), \quad (2.40)$$

$$SCL_{\text{std}} = \sqrt{\frac{1}{N-1} \sum_{n=1}^N \left(SCL(n) - SCL_{\text{mean}} \right)^2}. \quad (2.41)$$

Non Specific SCR Features Non specific SCRs (NSSCRs) are identified from the phasic component or from the SMNA driven SCR estimate. According to Baldini et al [29] SCRs have a 3-5 s latency before presenting in response to an external stimulus. Therefore, NSSCR peaks in SCR were calculated in the first 3 s after stimulus onset. Let $\{a_k\}_{k=1}^K$ denote the amplitudes of the K detected NSSCR peaks within the time window 0–3 s.

The following features are commonly used (Equation 2.42–Equation 2.45):

$$NS\text{-}SCR_n = K, \quad (2.42)$$

$$NS\text{-}SCR_{\text{peak}} = \max_{1 \leq k \leq K} a_k, \quad (2.43)$$

$$NS\text{-}Amp_{\text{sum}} = \sum_{k=1}^K a_k, \quad (2.44)$$

$$NS\text{-}SCR_{\text{mean}} = \begin{cases} \frac{1}{K} \sum_{k=1}^K a_k, & K > 0, \\ 0, & K = 0. \end{cases} \quad (2.45)$$

These indices capture, respectively, the number of non specific responses, their maximum amplitude, the global phasic output, and the average response magnitude in a given condition [29].

Stimulus Locked SCR Features In event related designs, SCR features can be linked to specific stimuli, either in the SCR or in the SMNA domain. SCR-related features were calculated starting from 3 s after stimulus onset until presentation of another stimulus. Let $\{a_k\}_{k=1}^{K_s}$ denote the amplitudes of SCR or SMNA peaks within the post stimulus window $3\text{--}stim_{dur}$ s, and let $stim_{dur}$ and t_{onset} be, respectively, the stimulus duration (in seconds) and the stimulus onset time. The following features are typically considered [29] (Equation 2.46–Equation 2.48):

$$SCR_n = K_s, \quad (2.46)$$

$$SCR_{peak} = \max_{1 \leq k \leq K_s} a_k, \quad (2.47)$$

$$Amp_{sum} = \sum_{k=1}^{K_s} a_k, \quad (2.48)$$

together with latency measures (Equation 2.49 and Equation 2.50):

$$Lat_1 = t_{k_1} - (t_{onset} + 3), \quad (2.49)$$

$$Lat_2 = t_{k^*} - (t_{onset} + 3), \quad (2.50)$$

where t_{k_1} is the time of the first significant SCR peak and t_{k^*} is the time of the peak with maximal amplitude, both calculated starting 3 s after the stimulus onset. These features are used to describe the timing and amplitude of phasic responses to discrete events.

Spectral Sympathetic Index In some experiments, the sympathetic activation was also characterized in the frequency domain by means of the EDAsymp feature [29, 323]. Let $PSD_{EDA}(f)$ denote the power spectral density of the EDA signal or of its tonic component. EDAsymp is defined as the power in the band 0.045–0.25 Hz (Equation 2.51):

$$EDAsymp = \int_{0.045}^{0.25} PSD_{EDA}(f) df. \quad (2.51)$$

This band is associated with sympathetic modulation of EDA and provides a global index of sympathetic arousal.

2.4.4 Nonlinear Complexity Analysis: Phase Space Reconstruction, Sample Entropy, and ComEDA

To complement conventional time and frequency domain metrics, in section 3.2, nonlinear complexity features were extracted from the EDA signal. Since both entropy based and phase space based measures depend on the temporal structure of the signal, the analysis was grounded on an initial reconstruction of the underlying dynamical system. The embedding parameters estimated from phase space reconstruction were then used to compute Sample Entropy (SampEn) for the tonic and phasic components. Finally, the spatial complexity of EDA dynamics was quantified using the ComEDA algorithm [323], which is particularly suited for ultra short and highly non stationary signals.

Phase Space Reconstruction Given a time series $\{x(1), x(2), \dots, x(N)\}$, which can be the cleaned EDA signal or its tonic or phasic component, the phase space is reconstructed using Takens' time delay embedding. For a given embedding dimension m and time delay τ , the embedding vectors are (Equation 2.52):

$$\mathbf{X}(k) = [x(k), x(k - \tau), x(k - 2\tau), \dots, x(k - (m - 1)\tau)], \quad (2.52)$$

for $k = 1, \dots, n$, with (Equation 2.53)

$$n = N - (m - 1)\tau. \quad (2.53)$$

The parameters m and τ are selected for each time series using, respectively, the False Nearest Neighbors (FNN) method and the first minimum of the auto mutual information function [323]. These embedding parameters were subsequently used for the computation of nonlinear entropy based features.

Sample Entropy of Tonic and Phasic Components The temporal complexity of the EDA signal was quantified using SampEn, a nonlinear measure of signal irregularity and unpredictability that is particularly suited for short and noisy physiological time series. Given a time series $\{x(1), x(2), \dots, x(N)\}$, SampEn estimates the negative logarithm of the conditional probability that two sequences of length m that are similar within a tolerance r remain similar when their length is increased to $m + 1$. The formal definition of SampEn

is given in Equation 2.54:

$$\text{SampEn}(m, r, N) = -\ln \left(\frac{A}{B} \right), \quad (2.54)$$

where B is the number of pairs of embedded vectors of dimension m whose mutual distance is smaller than r , and A is the corresponding number of pairs for dimension $m + 1$.

The distance between two embedded vectors $\mathbf{u}_i^m$ and $\mathbf{u}_j^m$ is computed using the Chebyshev norm (Equation 2.55):

$$d(\mathbf{u}_i^m, \mathbf{u}_j^m) = \max_{k=0, \dots, m-1} |x(i+k) - x(j+k)|. \quad (2.55)$$

The embedding dimension m and time delay τ used for SampEn computation were derived from the phase space reconstruction procedure described above, ensuring consistency with the intrinsic dynamics of the EDA signal. SampEn was computed separately for the SCL and the SCR components. Higher SampEn values indicate increased temporal irregularity and complexity of autonomic activity.

Angular Distances in Phase Space The distance between two phase space vectors $\mathbf{X}(i)$ and $\mathbf{X}(j)$ is defined through the cosine of the angle between them (Equation 2.56):

$$d_{ij} = \cos(\theta(\mathbf{X}(i), \mathbf{X}(j))) = \frac{\mathbf{X}(i) \cdot \mathbf{X}(j)}{\|\mathbf{X}(i)\|_2 \|\mathbf{X}(j)\|_2}, \quad (2.56)$$

for all $1 \leq i < j \leq n$. This angular distance is robust to the spiky nature of EDA and avoids the direct use of amplitude thresholds, which can be problematic for SCR like signals.

Probability Density Function of Distances The set of all d_{ij} values is used to estimate a probability density function (PDF) via a kernel density estimator with Gaussian kernel. The number of bins B for the PDF is chosen according to Sturges' rule. Let p_i denote the probability associated with the i th bin, so that (Equation 2.57):

$$\sum_{i=1}^B p_i = 1, \quad p_i \geq 0. \quad (2.57)$$

Quadratic Rényi Entropy and ComEDA Index The spatial complexity of the attractor is quantified by the quadratic Rényi entropy of the PDF [323] (Equation 2.58):

$$H_2 = -\log_2 \left(\sum_{i=1}^B p_i^2 \right). \quad (2.58)$$

To facilitate comparisons across different conditions and time series, H_2 is normalized to the interval $[0, 1]$ (Equation 2.59):

$$\text{ComEDA} = -\frac{1}{\log_2 B} H_2. \quad (2.59)$$

Higher ComEDA values correspond to a more uniform distribution of distances in phase space, that is, higher spatial complexity of EDA dynamics. This index was computed for the cleaned EDA signal.

2.5 ECG and Heart Rate Variability Analysis Methodology

In section 4.4, ECG activity was used to quantify autonomic responses associated with emotional and cognitive states. The processing methodology consisted of ECG preprocessing, R-peak detection using the Pan–Tompkins algorithm, reconstruction of a uniformly sampled instantaneous HRV signal using point-process modeling, and the extraction of standard linear and nonlinear HRV features.

2.5.1 R-Peak Detection: the Pan–Tompkins Algorithm

R-peak detection on the ECG signal was performed using the classical Pan–Tompkins operator [337], which is robust to noise and suitable for both short and long recordings. This algorithm remains one of the most widely adopted approaches for ECG QRS detection and provides a stable and reproducible framework for heartbeat identification, thereby limiting variability introduced by alternative detection strategies. The algorithm [389] consists of the following steps:

1. **Band-pass filtering** ($0.5 - 40\text{Hz}$) to emphasize the QRS complex;

2. **Differentiation**, defined in Equation 2.60:

$$y_d[n] = y[n] - y[n - 1], \quad (2.60)$$

3. **Squaring**, shown in Equation 2.61:

$$y_s[n] = (y_d[n])^2, \quad (2.61)$$

4. **Moving-window integration**, shown in Equation 2.62:

$$y_m[n] = \frac{1}{M} \sum_{k=0}^{M-1} y_s[n - k], \quad (2.62)$$

5. **Adaptive thresholding** for peak classification.

Detected R-peaks define the sequence of beat-to-beat intervals, as expressed in Equation 2.63:

$$RRi = tR, i + 1 - tR, i. \quad (2.63)$$

These intervals form the basis for HRV analysis.

2.5.2 Point-Process Modeling for Continuous HRV Reconstruction

Standard HRV analysis requires converting the irregularly sampled RR interval series into a continuous, uniformly sampled time series. In section 4.4, the instantaneous heart rate (IHR) and related quantities were estimated through a point-process probabilistic model following [30]. This method models R-peak occurrences as a stochastic point process whose conditional intensity function $\lambda(t)$ depends on past RR intervals, typically via an autoregressive (AR) structure.

Conditional Intensity Function Let t_k denote the sequence of R-peak times. The conditional intensity is modeled as shown in Equation 2.64:

$$\lambda(t|\mathcal{H}_t) = \frac{1}{\mu(t|\mathcal{H}_t)}, \quad (2.64)$$

where $\mathcal{H}_t$ denotes the ECG history up to time t . In an AR(p) structure, the expected waiting time $\mu(t)$ is given by Equation 2.65:

$$\mu(t) = \beta_0 + \sum_i 1^p \beta_i, RRk - i. \quad (2.65)$$

Online Estimation and Uniform Sampling The model parameters are estimated using local likelihood optimization, yielding the IHR in Equation 2.66:

$$\text{IHR}(t) = \frac{60}{\mu(t)}. \quad (2.66)$$

The IHR, also known as the instantaneous RR interval series, is then uniformly resampled at $f_s = 4$ Hz. This produces an HRV signal suitable for spectral and nonlinear analysis, without the distortions typically introduced by cubic spline interpolation or resampling of NN intervals.

2.6 Pupillometry Data Analysis

Raw pupil diameter (PD) signals may contain artifacts caused by blinking, corneal reflections, or temporary loss of tracking. Because pupillometric measures are particularly sensitive to blinking artifacts, tracking losses, and processing choices, the preprocessing pipeline described below was adopted to obtain a reliable pupillary time series and to limit variability introduced by signal reconstruction procedures; the steps applied in such pipeline for the study presented in section 4.3 were as follow:

1. **Artifact detection:** samples exceeding a threshold of 5 times the median absolute deviation (MAD) with respect to the median value were labelled as artifacts (Equation 2.67):

$$|PD(t) - \text{median}(PD)| > 5 \cdot MAD(PD) \quad (2.67)$$

2. **Interpolation:** missing or invalid samples were reconstructed using a shape-preserving cubic interpolation, namely the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP).
3. **Filtering:** the reconstructed signal was smoothed using a moving-average filter of window w samples to reduce high-frequency noise.
4. **Aggregation:** left and right pupil signals (which are highly correlated [241]) were averaged to obtain a single pupil diameter time series (Equation 2.68):

$$PD_{avg}(t) = \frac{PD_L(t) + PD_R(t)}{2} \quad (2.68)$$

2.6.1 Pupillometric Feature Extraction

After preprocessing, in section 4.3, pupillometric features were extracted from the cleaned PD signal to characterise both its overall magnitude and temporal dynamics. Linear and nonlinear descriptors were computed to capture complementary aspects of pupil behaviour, which is known to reflect cognitive load and autonomic nervous system activity.

Linear features Linear features were computed to describe the central tendency, dispersion and extreme values of the PD signal, as well as its temporal evolution. Specifically, the following metrics were extracted (Equation 2.69–Equation 2.72):

- Mean pupil diameter:

$$\mu_{PD} = \frac{1}{T} \sum_{t=1}^T PD(t), \quad (2.69)$$

where $PD(t)$ represents the pupil diameter at time t and T is the total number of samples;

- Standard deviation, quantifying pupil size variability:

$$\sigma_{PD} = \sqrt{\frac{1}{T} \sum_{t=1}^T (PD(t) - \mu_{PD})^2}; \quad (2.70)$$

- Minimum and maximum pupil diameter values, reflecting the extreme constriction and dilation levels reached during the task;
- Latency of minimum and maximum pupil diameter, computed as the temporal indices corresponding to these extrema (Equation 2.71):

$$t_{\min} = \arg \min_t PD(t), \quad t_{\max} = \arg \max_t PD(t). \quad (2.71)$$

These latencies were included to account for task-related processing load and response timing, which have been shown to be sensitive to cognitive demands [233];

- Pupil dilation velocity, defined as the first temporal derivative of the pupil diameter signal (Equation 2.72):

$$v(t) = \frac{dPD(t)}{dt}. \quad (2.72)$$

This feature provides information about the dynamic rate of pupil changes over time.

Nonlinear features Pupil diameter regulation involves both sympathetic and parasympathetic components of the autonomic nervous system, whose interactions can generate nonlinear and potentially chaotic dynamics. To capture these properties, the Largest Lyapunov Exponent (LLE) was computed as a measure of local instability and sensitivity to initial conditions. The LLE has been widely used in biomedical signal analysis to characterise local instabilities in physiological time series [435].

Since nonlinear dynamics were assessed from a single physiological time series, phase-space reconstruction was performed according to Takens' embedding theorem. The reconstructed state space was obtained by considering m delayed copies of the pupil diameter signal, separated by a time delay τ . The embedding dimension m was selected as the first minimum of the false nearest neighbours function, while the time delay τ was determined as the first minimum of the mutual information function [335].

After reconstructing the phase space, the Largest Lyapunov Exponent was estimated as in Equation 2.73:

$$LLE = \lim_{t \rightarrow \infty} \frac{1}{t} \ln \frac{d(t)}{d(0)} \quad (2.73)$$

where $d(0)$ and $d(t)$ represent the initial and time-evolved distances between neighbouring trajectories in the reconstructed space. A positive LLE indicates exponential divergence of nearby trajectories, reflecting chaotic dynamics or increased autonomic complexity, whereas a negative value suggests convergence.

2.7 Markov-Inspired Approach for Facial Expressions Dynamic Analyses

Traditional Markov Chain (MC) formulations [209] describe a stochastic process evolving over a finite set of discrete states, with transitions characterised by a transition probability matrix. Classical MC models assume that, at each time step, the system occupies a single discrete state from a predefined set and that transitions between states satisfy the Markov property. In section 4.4, a MC-inspired approach to model subjects' continuous emotional

space is adopted. Following Ekman’s emotion taxonomy [136,138], each time point is represented by a 7-dimensional probability vector associated with the canonical FEs (namely *angry*, *disgust*, *fear*, *happy*, *neutral*, *sad*, *surprise*). Instead of discretising these vectors into single emotion labels, their graded nature is preserved and temporal dynamics directly within this continuous space are modeled. To characterise emotion transitions, a *transition co-occurrence matrix* (TCM) is constructed by accumulating outer products of consecutive FE vectors (Equation 2.74),

$$TCM = \sum_{n=1}^{N-1} [FE_n^T \times FE_{n+1}] \quad (2.74)$$

Each element $TCM_{i,j}$ quantifies the empirical co-activation between emotion component i at time n and component j at time $n + 1$. After row-wise normalisation, the resulting matrix is interpreted as a *continuous-state Markov transition operator* acting on the emotional probability space. This operator captures temporal dependencies between FE distributions while avoiding the artificial discretisation imposed by classical finite-state MC models.

The resulting TCM summarise the temporal evolution of each subject’s emotional profile throughout the task sequence while preserving the probabilistic structure of the FE outputs. Each TCM is then row-normalized with the sum of each row (Equation 2.75):

$$T\hat{C}M = TCM \oslash TCM \times J, \quad (2.75)$$

where $\oslash$ denotes element-wise division, and J is the all-ones matrix. Finally, each element of the TCM represents the probability of moving from one emotional state to another. All main diagonal elements represent the probability of remaining in the same emotional state. All other elements represent the transition probabilities from one state to another. If one or multiple of the seven considered FE present a null probability of being reached, these are discarded from further analysis, and $T\hat{C}M$ size is reduced accordingly. Finally, the sub-chain probability (SC_P) is computed to account for possible transient states (*i.e.* states which have null probabilities of being reached in a finite number of steps).

From the SC_P continuous-state operator a total of ten standard Markov metrics were calculated as reported below in Equation 2.76–Equation 2.80:

- Entropy Rate (ER), which is calculated as reported in Equation 2.76

and Equation 2.77 [96];

$$ER(SC_P) = \sum_i \mu_i e_i, \quad (2.76)$$

where:

$$e_i := - \sum_j p_{ij} \log p_{ij}, \quad (2.77)$$

is the entropy associated with each state and μ_i is the asymptotic distribution of the chain;

- Stability (St), which is computed as the mean values of the SC_P matrix diagonal elements (Equation 2.78):

$$St(SC_P) = \frac{\sum_{n=1}^N p_{i,i}}{N}; \quad (2.78)$$

- Spectral Gap (SpG), which is the difference, in absolute values, of the two highest eigenvalues of the SC_P [301] (Equation 2.79):

$$SpG = |\lambda_1 - \lambda_2|; \quad (2.79)$$

- Mean Hitting Time (MHT): considering the i -th state, the MHT is calculated as the average of hitting times needed to reach the i -th state for the first time, starting from any state (Equation 2.80):

$$MHT_i(SC_P) = \frac{\sum_{n=1}^N mht_{i,n}}{N}. \quad (2.80)$$

2.8 Data Acquisition Systems

The experimental activities carried out during this doctoral research were centered on the validation of a multimodal acquisition system (endorsement of compliance with the Opinion of the Ethics Committee for Research no. 275 of 04/09/2023), specifically designed to be modular and adaptable according to the research hypothesis and experimental context. The primary objective of validating such a system was to ensure high ecological validity, thereby maximizing participant comfort and minimizing the intrusiveness of the setup, while also optimizing acquisition and data management efficiency.

To this end, the system relied predominantly on wearable, comfortable, non-invasive, and lightweight devices, allowing participants to focus on the experimental tasks with minimal distraction. Despite these advantages, wearable technologies inherently present some limitations, including restricted battery life, lower signal-to-noise ratios, and non-transparent calibration procedures that often depend on manufacturer-specific implementations. A crucial requirement of this research was to enable direct or indirect communication among all sensors used, in order to achieve precise temporal synchronization across modalities. Accurate synchronization was essential to segment physiological signals according to salient temporal markers associated with task events. In some cases, this was facilitated by employing sensors produced by the same manufacturer, which ensured compatibility through validated communication protocols. In other setups, synchronization had to be reconstructed offline, by identifying salient markers and aligning them across signals recorded at different sampling frequencies.

2.8.1 EEG Systems

Throughout the doctoral work, neural activity was recorded using two different EEG systems:

- **DSI-24 (Wearable Sensing, San Diego, CA, USA):** a 24-channel, 19 of which are EEG channels, wireless dry-electrode headset (Figure 2.4, left), providing $f_s = 300Hz$ and rapid setup. The raw EEG signals recorded by the DSI-24 are all referred to the Pz electrode, and the other 18 EEG electrode locations follow the international 10-20 layout: Fp1, Fp2, Fz, F3, F4, F7, F8, Cz, C3, C4, T3, T4, T5, T6, P3, P4, O1, O2. The system can integrate external EDA (see subsection 2.8.2), ECG and respiration modules, allowing for auxiliary physiological measurements within the same hardware unit;
- **SAGA 32+ (TMSi, Oldenzaal, Netherlands):** a 32-channel gel-based amplifier (Figure 2.4, right), used for high-density and low-noise neural recordings. It provides sampling frequency up to $1000Hz$, and electrode placement follows the international 10-20 layout.

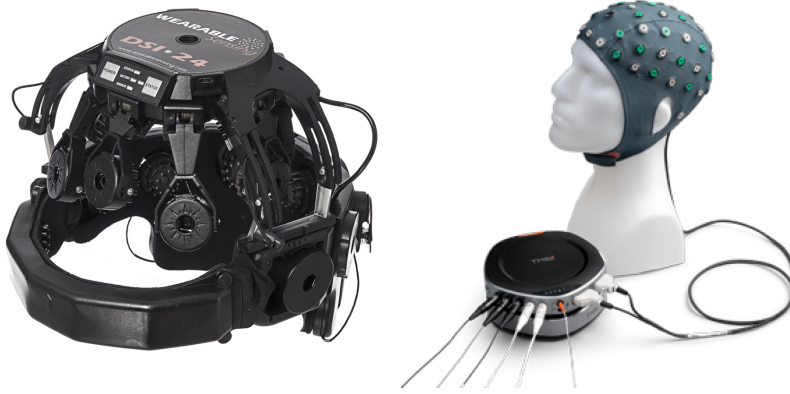


Figure 2.4: EEG acquisition systems used in the project: DSI-24 dry-electrode system (left) and SAGA 32+ gel-based system (right).

2.8.2 Autonomic Nervous System Systems

Autonomic activity was monitored using Shimmer3 sensors (Shimmer Sensing, Dublin, Ireland) and complementary low-cost modules, depending on the required flexibility:

- **EDA:** acquired using the DSI-24 external EDA module (Figure 2.5) and, in specific configurations, via a Grove GSR module connected to an Arduino MKR WiFi 1010 board (Figure 2.6). EDA electrodes were consistently placed on the medial phalanges of the index and middle fingers belonging to the non-dominant hand to maximize signal-to-noise ratio;
- **ECG:** recorded using Shimmer3 ECG units (Shimmer Sensing, Dublin, Ireland) (Figure 2.7) and RUSA textile sensors (Smartex, Pisa, Italy) with fully integrated fabric electrodes and a dedicated SEW acquisition module (Figure 2.8).

2.8.3 Pupillometry, Voice and Facial Expression Data

Pupillary activity was monitored using Tobii Pro Glasses 3 (Tobii, Stockholm, Sweden, Figure 2.9), which provided real-time gaze estimation, pupil

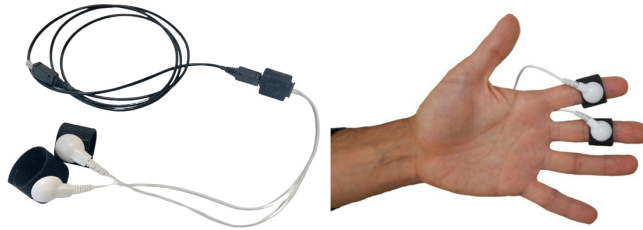


Figure 2.5: DSI-24 GSR external module (left) and proper positioning of the electrodes on the non-dominant hand of subjects (right).

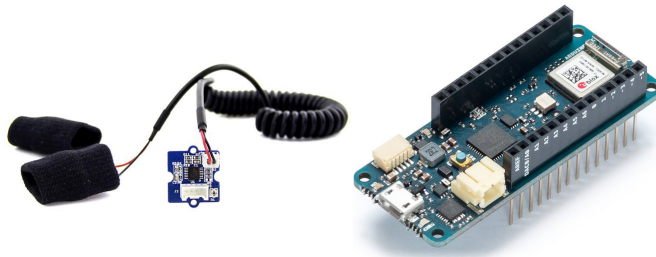


Figure 2.6: Grove GSR module (left) and Arduino MKR WiFi 1010 (right) used for EDA acquisition.

diameter, and scene recording. The system allowed free head movement and was therefore suitable for semi-naturalistic experiments and interactive tasks.

Voice recordings were acquired using the Shure SM58 (Shure Inc., Niles, IL, USA) to capture speech at $f_s = 44.1kHz$. The microphone was connected to the TASCAM-366 audio interface (TASCAM, Tokyo, Japan) which allowed for computer recording through a USB port connection (Figure 2.10).

FE data were collected using integrated or externally mounted webcams positioned on or near the stimulus presentation screen. These cameras captured the participants' FEs throughout the experimental tasks. Continuous screenshots of the face ($f_s = 1Hz$) were subsequently analyzed using the Web-Agile Facial Emotion Recognition (WAFER) system [180], a browser-based framework capable of identifying and classifying FEs into the seven basic emotions postulated by Ekman's theory of emotions (*angry*, *disgust*, *fear*, *happy*, *neutral*, *sad* and *surprise*) [135]. The outputs of this analysis



Figure 2.7: Shimmer3 devices used for EDA and ECG acquisition.



Figure 2.8: RUSA Wearable fabric-electrode ECG strap band.

were expressed as percentage probabilities for each emotion, summing up to 100%.

2.8.4 Synchronization Infrastructure

Temporal synchronization across different signal recordings was achieved using the Wearable Sensing Wireless Trigger Hub (Wearable Sensing, San Diego, CA, USA, Figure 2.11). Two synchronization mechanisms were employed:

- **Hardware push-button:** sending a digital trigger simultaneously to EEG devices and auxiliary sensors;
- **Photodiode-based triggering:** a photodiode placed on the stimulus



Figure 2.9: Tobii Pro Glasses 3 used for pupil-based measurements.



Figure 2.10: TASCAM-366 audio interface (left) and Shure microphone (right) used for voice recordings.

monitor detected the onset of white/black markers rendered by the presentation script, enabling alignment of visual events with recorded data at millisecond precision.

Other synchronization techniques included manual alignment with the devices' timestamp and manual trigger reconstruction using the video recording of Tobii Pro Glasses3.

2.8.5 Data Management and Processing

All signals were processed using MATLAB (The MathWorks, Inc., Natick, MS, USA) and dedicated toolboxes, such as EEGLAB [120] and Biovoice [315], or implemented algorithm such as cvxEDA [88,176] and Pan-Tompkins

Japanese participants' emotional state before, during and after playing two digital games. In this context, the Italian version of PANAS, validated by Terraciano et al., was administered to Italian participants [427]. This version of the scale demonstrated an internal reliability coefficient of $\alpha = 0.76$ [427]. For Korean participants, a modified PANAS version was used, differing from the original by including 11 negative and 9 positive items. According to Lee et al., this adjustment was made due to the cultural interpretation of the word "Alert," which carries a negative comprehension in Korean [261]. This version demonstrated reliability scores of 0.88 for positive affect and 0.87 for negative affect [261]. Finally, the Japanese version of PANAS, validated by Kawahito et al., was employed for Japanese participants [377]. This adaptation retained the original structure of 10 positive and 10 negative items, with reliability coefficients of 0.87 for positive affect and 0.88 for negative affect [377].

SAM In chapter 5 the Self-Assessment Manikin (SAM) [54] provided a nonverbal, pictorial measure of participants' momentary emotional reactions along three core affective dimensions: Valence, Arousal, and Dominance. The pictorial nature of SAM reduces cognitive load and linguistic biases, allowing participants to quickly and intuitively report their perceived emotional state. This was particularly advantageous in experiments involving cognitive demands, immersive virtual environments, or rapid stimulus presentation, where verbal reporting could disrupt the task structure or introduce confounds. SAM scores were crucial for linking the subjective perception of emotional impact to objective physiological responses such as EDA responses and EEG-derived markers of engagement. Moreover, the dominance dimension offered insights into self-perceived control and agency, aspects that proved relevant in studies examining participants' responses to challenging or emotionally evocative scenarios.

IRI To extend the analysis from affective perception to trait-level empathic functioning, in section 5.1 the research also employed the Interpersonal Reactivity Index (IRI) [115]. The IRI is one of the most comprehensive self-report tools for assessing empathy, conceptualized as a multidimensional construct comprising both cognitive and affective components. It consists of four subscales, each capturing distinct but complementary facets of interpersonal sensitivity:

- Perspective Taking (PT), assessing the tendency to spontaneously adopt others' psychological viewpoints;
- Fantasy (FS), reflecting the propensity to imaginatively transpose one-self into fictional situations;
- Empathic Concern (EC), measuring feelings of warmth, compassion, and concern for others;
- Personal Distress (PD), evaluating self-oriented feelings of discomfort and anxiety in tense interpersonal contexts.

This four-dimensional structure is widely recognized in the literature and provides a nuanced description of empathy that aligns with contemporary frameworks distinguishing cognitive empathy, affective resonance, and self-oriented distress [117,307]. Within the present research, the IRI offered a trait-level index of empathic predisposition that could modulate participants' perceptual, emotional, and physiological responses to stimuli. For example, higher empathic concern has been associated with stronger autonomic engagement when observing emotionally salient scenes, whereas high personal distress can relate to increased physiological arousal but reduced regulatory control.

QCAE, TAS 20, SPS and SIAS To explore empathic dispositions, in the cross-biofeedback hyperscanning affective task reported in section 5.3, four questionnaires were administered to volunteers. The Questionnaire of Cognitive and Affective Empathy (QCAE) [185] was administered as a multidimensional tool capturing two core components of empathy: Cognitive Empathy (CE), reflecting the ability to understand and infer others' mental and emotional states, and Affective Empathy (AE), denoting emotional responsiveness and resonance with others' experiences. In addition to empathy-related constructs, the Toronto Alexithymia Scale (TAS 20) [196] was employed to evaluate individual differences in emotional awareness and the ability to identify and describe one's own affective states. Given its three-factor organization, encompassing difficulty identifying feelings, difficulty describing feelings, and externally oriented thinking, the TAS 20 provided a trait-level index of emotional processing styles. Finally, the assessment of social anxiety was refined through the combined use of the Social Phobia Scale (SPS) [196] and the Social Interaction Anxiety Scale (SIAS) [361]. While

the SPS captures fears related to being observed and negatively evaluated by others, the SIAS targets anxiety arising in direct interpersonal encounters. Their complementary nature allowed for a detailed differentiation between evaluative and interactional components of social anxiety, dimensions that are known to modulate stress reactivity, attentional deployment, and autonomic arousal.

Chapter 3

Neurophysiological Responses to Natural and Non-Natural Stimuli: From Faces to Lexical Units

This chapter investigates how the human nervous system processes perceptual and linguistic stimuli that differ in authenticity and semantic content, by integrating central and autonomic physiological measures. Two experimental paradigms are presented, distinct in modality but conceptually aligned in their contrast between natural, meaningful stimuli and non-natural or non-meaningful counterparts. The first paradigm focuses on face processing, comparing neural responses to real faces and deepfakes displaying different emotional expressions. Using the EEG, the study examines ERPs and power spectral activity associated with perceptual authenticity and affective processing, providing insight into how synthetic visual content is discriminated at the neural level. The second paradigm addresses speech and language processing through a controlled repetition task contrasting existing words and pseudowords. By combining EEG markers of semantic and phonological processing, EDA as an index of sympathetic arousal, and acoustic features of voice production, this study characterizes cognitive load and speech-related effort in the

*absence of lexical-semantic information. These paradigms offer complementary perspectives on how the brain and peripheral systems respond to stimuli that vary in familiarity, realism and meaning, contributing to the understanding of natural versus non-natural information processing.*¹

Human cognition is fundamentally grounded in the capacity to extract structure and meaning from sensory inputs under varying degrees of familiarity, semantic content and contextual relevance. Even in highly constrained experimental conditions, perceptual and cognitive processing emerges from the interaction between central neural mechanisms and peripheral autonomic regulation. For this reason, paradigms based on simple and well-controlled stimuli provide an essential starting point for characterizing the basic psychophysiological organization that underlies more complex cognitive, emotional and social behaviors. This chapter presents two experimental studies that constitute the most controlled level of the experimental program developed in this thesis. As outlined in the global structure of the work, these paradigms serve as a reference point for subsequent chapters by isolating fundamental processes of perception and cognitive evaluation while minimizing task demands, contextual ambiguity and social interaction. Despite their simplicity, both paradigms are specifically designed to probe how the human nervous system responds when confronted with stimuli that differ in familiarity, identifiability or semantic grounding. The first study focuses on face processing, a highly specialized and evolutionarily salient human ability. Faces represent a privileged category of visual stimuli, rapidly conveying information about identity and emotional state. In this paradigm, the contrast between real human faces and AI-generated synthetic faces allows the investigation of how perceptual authenticity and emotional expression modulate neural responses under controlled viewing conditions. By relying on high-temporal-resolution EEG measures, the study targets early and in-

¹The section 3.1 of this chapter has been published as “Real and deepfake face recognition: An EEG study on cognitive and emotive implications” in *Brain Sciences*, vol. 13, iss. 9, pp. 1233, 2023 [424]. The section 3.2 of this chapter has been published as “Event-Related Potentials in Complex and Simple Words-Pseudowords Aloud Reading Task” in *46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, vol. 2024, pp. 1–4, 2024 [422] and as “Electrodermal activity and acoustical analysis in a words/non-words reading task” in *Models and Analysis of Vocal Emissions for Biomedical Applications: 13th International Workshop*, pp. 99–102, 2023 [64].

intermediate stages of perceptual and evaluative processing, offering insight into the neurophysiological mechanisms engaged when natural and artificial visual stimuli are discriminated. The second study addresses speech and language processing through a structured word and pseudoword repetition task. Pseudowords constitute a canonical tool in psycholinguistic and clinical research, as they preserve phonological plausibility while removing lexical-semantic content. This paradigm enables the selective engagement of phonological encoding, working memory and articulatory planning, providing a controlled manipulation of cognitive load without introducing semantic variability. In this context, the integration of EEG, electrodermal activity and acoustic voice features allows the joint examination of neural dynamics, autonomic arousal and speech production characteristics during linguistic processing. Although the two paradigms differ in sensory modality and task demands, they share a common conceptual framework. Both contrast meaningful, familiar or natural stimuli with counterparts that are non-semantic, unfamiliar or artificial, and both examine how such contrasts shape central and peripheral physiological responses. From a broader perspective, these studies address a core question that recurs throughout the thesis: to what extent psychophysiological markers reflect general principles of cognitive organization versus domain-specific processing mechanisms. By establishing a baseline characterization of neural and autonomic responses in minimal experimental settings, this chapter provides a foundation for interpreting the more complex and ecologically enriched paradigms presented in the following chapters. The patterns identified here serve as reference points against which the modulation introduced by active task engagement, emotional content and social interaction can be evaluated, supporting a coherent and progressive interpretation of psychophysiological dynamics across contexts.

3.1 Real and Deepfake Face Recognition an EEG Study on Cognitive and Emotive Implications

3.1.1 Introduction

The human brain's ability in face processing (FP) is crucial, as the decision on how to interact with other individuals mainly depends on the outcome

of the recognition process [340]. Face recognition (FR) is a cognitive process whereby humans identify and discriminate between individuals based on facial features; its abilities vary across individuals and can be influenced by experience, familiarity, and attentional focus [211]. It involves activating and integrating specialized brain regions, such as the fusiform face area (FFA), which plays a key role in face processing [218]. Neural networks within the FFA extract relevant facial information, enabling the encoding and retrieval of facial representations from memory. The FFA, localized within the fusiform gyrus (FG), is responsible for extracting the consistent elements of facial features and their spatial arrangements that are inherently linked to a person's identity. Specifically, the FFA is highly specialized in analyzing and discerning facial features, enabling the recognition and differentiation between individuals' faces. The FFA showed increased activation when individuals perceive faces, in contrast to other objects or stimuli [25]. Faces can also be differentiated for their emotional content, and previous studies have largely investigated the recognition processes of face emotional expressions [4, 194].

Early models of face perception, such as the influential model proposed by Bruce and Young [61], revealed distinct pathways for perceiving and recognizing different aspects of personal attributes from faces, including identity, emotion, and facial speech. According to these models, separate cognitive processes were involved, contributing to the overall understanding of FP. Observing emotional expressions on another person's face allows to gather information about the emotions they are experiencing and elicit similar emotional responses within ourselves. The perception of emotional expressions plays a vital role in social interactions and has been shown to activate brain regions involved not only in perceiving facial stimuli but also in experiencing one's own emotions [194]. It suggests a close link between the perception of emotions in others and our own emotional experiences, highlighting the intricate relationship between social cognition and emotional processing. According to Adolphs [3], several brain regions involved in basic emotion recognition, including the temporo-occipital, orbito-frontal, and right parietal cortices, are engaged in processing the perceptual aspects and the emotional significance of stimuli. These regions are crucial in perceiving and analyzing the visual information of stimuli and assigning emotional value and significance to them. It suggests that these brain regions are involved in the integrated processing of perceptual and emotional aspects of stimuli.

Brain regions can be categorized as 'affective' or 'cognitive'. However, it is evident that the brain regions typically associated with affective processes also play a role in cognition, and those considered cognitive regions also contribute to emotions. Noteworthy, cognition and emotion are strictly integrated and a complex cognitive-emotional dynamic exists among various brain networks. Emotion and cognition strongly influence behavior. Furthermore, the neural basis of emotion and cognition is highly interconnected and should be viewed as non-modular, with minimal capacity for decomposition [345].

In recent years, the rapid development of artificial intelligence (AI) has given rise to a concerning phenomenon known as deepfakes. Deepfakes are realistic digital media content, particularly images or videos, that portray false information and can be created from scratch or by modifying authentic content through deep learning algorithms. Media advanced creation technologies based on deep learning algorithms are universally acknowledged as a serious threat to a person's reputation and digital identity, and, as the prevalence of deepfakes continues to grow, it becomes crucial to investigate their potential effects on human perception and cognition [319].

In the last decades, the human ability to distinguish between real and AI-generated faces has been investigated. Specifically, neuroscience research focused on how synthetic stimuli affect people's capacity for face recognition tasks [98]. Multimedia forensic research investigated how much face-mixing operations (i.e., a face manipulation where two faces are mixed to create a hybrid one carrying traits of both original faces) are perceived by people. Ensuring restricted access to locations or services is of utmost importance, particularly in the context of face authentication systems, to prevent unauthorized entry [285]. Several studies [147, 202, 236, 283] have reported that humans can still generally detect AI-generated media content correctly.

Recently, studies on EEG correlates investigated viewers' ability to distinguish familiar and unfamiliar people from their face-swapped counterparts. Results showed that it is possible to discriminate fake videos from genuine ones when at least one face-swapped actor is known to the observer [425].

Synthetic faces can also exhibit a broad range of emotions. Investigation of brain reactions to facial expressions is becoming a widespread research area, aiming to better understand emotional processing and cognitive mechanisms. Even though traditional models suggest that facial identity and expression are processed in distinctive brain areas, the current findings high-

light that emotion processing can strongly influence facial recognition and memory mechanisms [2]. Finally, other studies have shown that FP in adults is modulated by the emotional relevance of faces, especially those with expressions of fear [265].

The main objective of this work is to explore the capacity of individuals to discriminate between real and fake faces generated by AI, with a particular focus on emotional expressions. This research is also motivated by the need to better understand the implications of deepfakes on human perception and the potential challenges they pose to distinguish between authentic and manipulated visual stimuli. Neural correlates of face processing and emotion recognition are investigated. Moreover, ERPs are evaluated as they offer a valuable understanding of the timing and neural mechanisms that underlie cognitive functions like perception, attention, and memory, with a high level of temporal precision. section A.1 reports all the 60 faces used for the stimulation (Figure A.1) and the statistical analysis outcomes for the PSD-related feature for the emotional comparison (Figure A.2 and Figure A.3).

3.1.2 Materials and Methods

Participants In total, 45 healthy volunteers were involved in the experimental sessions, but only 23 of them (13 F and 10 M; mean age = 24.7 years, std age = 2.8 years, median age = 25 years, age range = 19 to 29 years) were included in the study analyses. All subjects reported normal or corrected-to-normal visual acuity. This study was approved by the Institutional Review Board (endorsement of compliance with the Opinion of the Ethics Committee for Research no. 275 of 04/09/2023), and all participants gave written informed consent.

Experimental Protocol Volunteers were subjected to 60 grayscale visual stimuli representing human faces, both synthetic or real, and expressing positive, neutral, or negative emotions. During the experimental session, room temperature (25°C) and illumination condition (~7800 lumen) were maintained constant; subjects were asked to sit on a chair, and the distance between the subject’s head and monitor was 60 cm. All images were resized to have fixed dimensions (1024 pixel × 1024 pixel) and resolution (96 dpi) and were presented centered over a uniform background on the screen of a 24-inch full high-definition (HD) monitor. Real stimuli were selected from a set of Caucasian faces (age range: 20–50 years) included in the CK+

face database [276] by looking at the arousal and valence scores. The same face dataset was used for all participants, who were unfamiliar with the presented faces.

Synthetic faces were generated through a generative-AI algorithm (i.e., FaceMix) [1] by mixing together 4 grayscale real images, all expressing the same type of emotion, randomly sampled each time from the real faces set. Stimuli were presented only once, balanced in sex, type of emotional facial expression (positive, neutral, negative), and type of image, i.e., synthetic or real. The dataset comprised three classes, specifically, the synthetic class, real class, and emotional class, where the latter included both real and synthetic faces split for the 3 different emotional expressions. Volunteers sat on a chair wearing an EEG helmet in front of a monitor where stimuli were presented. The experimental protocol was composed of two phases, as shown in Figure 3.1.

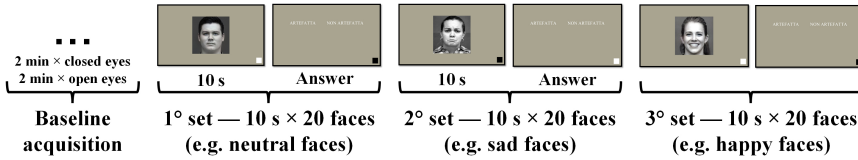


Figure 3.1: Face recognition experimental protocol timeline.

The first phase was a 4 min baseline acquisition with 2 min of closed and 2 min of open eyes. In the second phase, subjects observed 60 images of faces (for a complete overview, please refer to Figure A.1 in section A.1), composed by 3 sets of 20 faces (10 real and 10 synthetic). Each set contained faces associated exclusively with a polarized mood: positive (happy or smiling faces, Figure 3.2a,b and Figure A.1a), referred to as "happy"; neutral (relaxed faces, neutral expressions, Figure 3.2c,d and Figure A.1b); or negative (sad, angry or discomforted faces, Figure 3.2e,f and Figure A.1c), referred to as "sad". Both faces and sets were presented randomly for each subject. Each face was observed for 10 seconds by the subject, who was requested to finally press "z" or "m" on a keyboard if the presented stimuli were, respectively, considered synthetic or real. Image presentation and response times were, respectively, managed and recorded through the software interface.

EEG monitoring and acquisition were performed through the DSI-24 helmet (Wearable Sensing, San Diego, CA, USA), wirelessly connected to the



Figure 3.2: Example of synthetic (a,c,e) and real (b,d,f) faces expressing positive (a,b), neutral (c,d), and negative emotions (e,f) used as stimuli.

Trigger Hub (Wearable Sensing, San Diego, CA, USA) for synchronization purposes by means of a photodiode applied to the screen. EEG and trigger data were collected at a sampling frequency of 300 Hz (see subsection 2.8.1).

Signal Processing Chain EEG data were analyzed in MATLAB environment through EEGLAB [120] for continuous and event-related EEG processing. EEG signals were pre-processed following the standardized HAPPE workflow [164], as previously described in subsection 2.3.1 (band-pass filtering 1–45 Hz). After performing HAPPE (Figure 3.3), EEG signals were split into 10 s epochs, one for each presented face. Of the total 1360 extracted epochs (Table 3.1), 1224 were retained for further analysis (Table 3.2), while 136 were excluded by segmentation and rejection processes.

Statistical Analysis For each epoch, the average power spectrum in the 6 frequency bandwidths of analysis (i.e., delta, 1–4 Hz; theta, 4–7 Hz; alpha, 8–12 Hz; low-beta, 13–17 Hz; high-beta, 18–32 Hz; gamma, 32–48 Hz) was computed with a 300-point fast Fourier transform (FFT) without overlap.

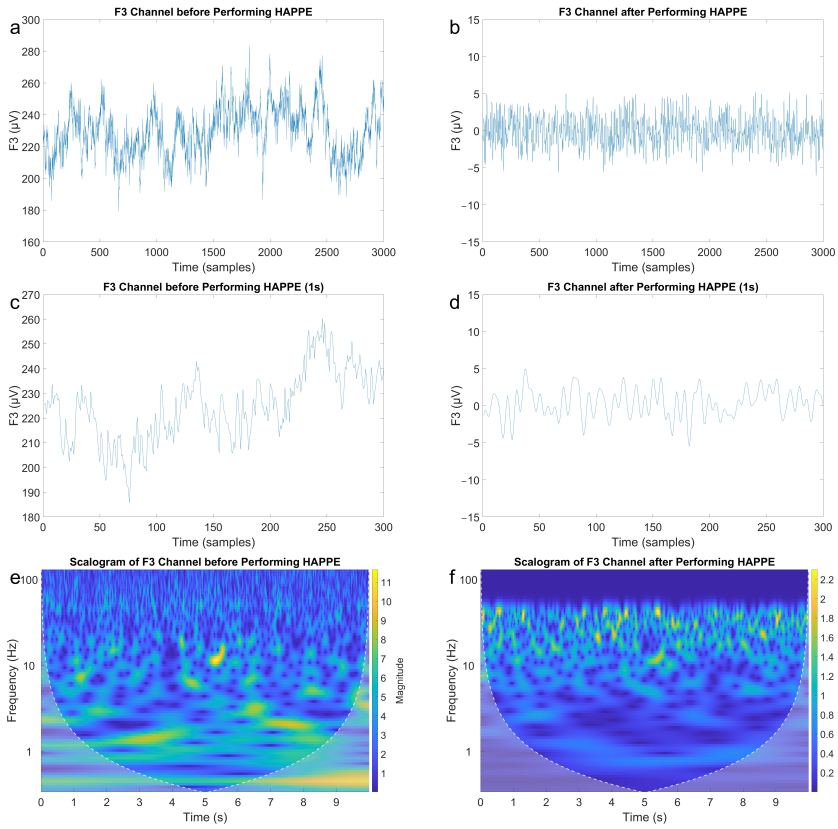


Figure 3.3: Example of EEG data from P3 channel before (a,c,e) and after (b,d,f) performing HAPPE.

PSD-related features were computed as the relative power densities for each band by normalizing the mean power spectra of each band by the power spectrum mean value in the 1–48 Hz range [316].

The event-related potential (ERPs) analysis were conducted without performing baseline correction [119]. The N100 (80–120 ms) [275], P100 (90–140 ms) [299], face-specific N170 (140–210 ms) [317], and N250 (200–300 ms) [388] and early P300 (300–400) [317] components were investigated in left temporo-occipital (LTO, includes T3, T5, and O1 channels), right temporo-occipital (RTO, includes T4, T6, and O2 channels), left frontal (LF, includes F3 and F7 channels), and right frontal (RF, includes F4 and F8 channels) areas. For each ERP component, the total area and the latency were computed for every subject, as previously described in subsection 2.3.2.

Epochs were labeled as follows to facilitate further analysis:

- Happy—in these epochs, the presented face expressed a "happy" emotion;
- Neutral—in these epochs, the presented face expressed a neutral emotion;
- Sad—in these epochs, the presented face expressed a "sad" emotion;
- tt (i.e., true–true)—in these epochs, the presented face was real, and the subject's answer was "real";
- ff (i.e., false–false)—in these epochs, the presented face was synthetic, and the subject's answer was "synthetic";
- tf (i.e., true–false)—in these epochs, the presented face was real, and the subject's answer was "synthetic";
- ft (i.e., false–true)—in these epochs, the presented face was synthetic, and the subjects' answer was "real".

Since the EEG-related PSD-extracted features were not normally distributed according to the Shapiro–Wilk test, surrogate tests were performed for statistical analysis [145]. The bootstrap method was performed to estimate statistics by sampling the dataset with replacement. After performing bootstrap statistics, a paired *t*-test was carried out to verify whether the mean values of the parameters were statistically different at a significance

Table 3.1: Epochs division according to labels before HAPPE.

Epochs Label	tt	ff	tf	ft	Total	Percentage
happy	173	172	57	58	460	33.3%
neutral	180	181	50	49	460	33.3%
sad	171	172	59	58	460	33.3%
total	524	525	166	165	1380	100%
percentage	38%	38%	12%	12%	100%	

Table 3.2: Epochs division according to labels after HAPPE.

Epochs Label	tt	ff	tf	ft	Total	Percentage
happy	148	151	51	45	395	32.3%
neutral	159	162	45	43	409	33.4%
sad	158	153	56	53	420	34.3%
total	465	466	152	141	1224	100%
percentage	38%	38.1%	12.4%	11.5%	100%	

level of 95% ($p < 0.05$). For emotional comparisons, a post hoc Bonferroni correction was performed.

As for the ERP statistical analysis, the Shapiro–Wilk test was also performed on total area and latency features. If both conditions under comparison were normally distributed, a paired t -test was used, or the Wilcoxon rank-sum test was performed. For emotional comparisons, a post hoc Tukey–Kramer correction was performed. Statistical comparison tests were organized as follows:

- Imfalse vs. Imtrue: comparison between synthetic and real stimulation.
 - HappyF vs. HappyT: comparison between synthetic happy and real happy stimulation.
 - NeutralF vs. NeutralT: comparison between synthetic neutral and real neutral stimulation.
 - SadF vs. SadT: comparison between synthetic sad and real sad stimulation.
- Happy vs. Neutral: comparison between happy vs. neutral emotions

- Imfalse_H vs. Imfalse_N: comparison between synthetic happy vs. synthetic neutral emotions.
- Imtrue_H vs. Imtrue_N: comparison between real happy vs. real neutral emotions
- Happy vs. Sad: comparison between happy vs. sad emotions
 - Imfalse_H vs. Imfalse_S: comparison between synthetic happy vs. synthetic sad emotions
 - Imtrue_H vs. Imtrue_S: comparison between real happy vs. real sad emotions
- Neutral vs. Sad: comparison between neutral vs. sad emotions
 - Imfalse_N vs. Imfalse_S: comparison between synthetic neutral vs. synthetic sad emotions
 - Imtrue_N vs. Imtrue_S: comparison between real neutral vs. real sad emotions

3.1.3 Results

This section reports on the statistical results regarding PSD and ERP features. In the first subsection, results of power spectrum analysis delta, theta, alpha, low-beta, high-beta, and gamma bands are shown, while in the second subsection, the results of the ERP analysis are reported.

Power Spectrum Analysis

Power spectrum statistical analysis is reported through scalp topographic maps (STMs). STMs describe the spatial distribution of extracted parameters, computed at the electrode position, across the brain. To simplify visualization, false-colors STM (FCSTMs) highlighting the statistically significant areas ($p < 0.05$, $p < 0.01$ and $p < 0.001$) were used. Non-significant areas were standardized with the color grey. The FCSTM represents the p -value of the paired t -test comparing the averages of the two conditions under investigation. If an area of the FCSTM assumes warm colors (yellow, orange, red), the first term of the comparison is statistically greater than the second one; on the contrary, if the area assumes cold colors (cyan, light blue, blue) the second term is statistically greater than the first.

Moreover, in this study, a set of stimuli that integrated cognitive and emotional processes was proposed. This complex set of stimuli required a specific investigation on the brain dynamic and the temporal resolution of FR process. Therefore, epoch analysis was performed on three different time intervals: 0–5 s, 5–10 s, and 0–10 s, allowing an interesting comparison among the first half (0–5 s), the second half (5–10 s), and the entire epoch (0–10 s) durations.

Originality comparison As for the "Imfalse vs. Imtrue" comparison, results of statistical analysis, as reported by Figure 3.4 (0–5 s), Figure 3.5 (5–10 s), and Figure 3.6 (0–10 s), show significant delta activation for deep-fakes in the frontal (Figure 3.5a and Figure 3.6a) and right occipital areas (Figure 3.4a, Figure 3.5a and Figure 3.6a); also, the left temporal area (Figure 3.5e and Figure 3.6e) shows significant high-beta activations for deep-fakes, whereas significant turn-ons for real faces are shown in theta in the right frontal area (Figure 3.4b and Figure 3.6b), in alpha in the right occipital (Figure 3.4c and Figure 3.6c) and left central areas (Figure 3.4c, Figure 3.5c and Figure 3.6c), and in high-beta and gamma in the right parietal area (Figure 3.5e,f and Figure 3.6e,f).

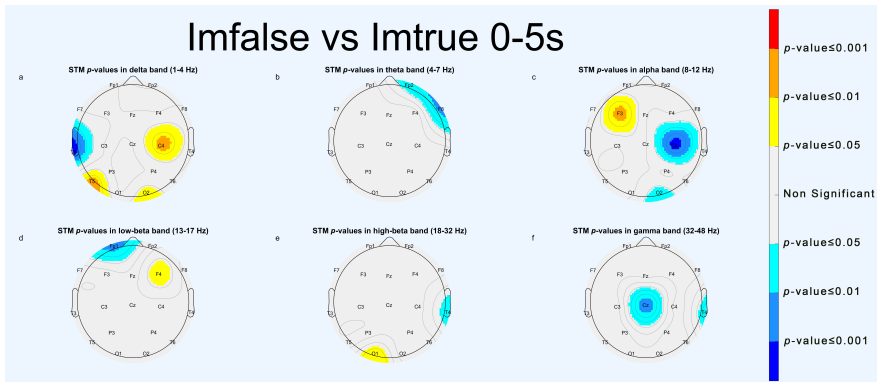


Figure 3.4: STMs of significant statistical activation of brain areas for "Imfalse vs. Imtrue" comparison (0–5 s). (a) delta band, (b) theta band, (c) alpha band, (d) low-beta band, (e) high-beta band, (f) gamma band.

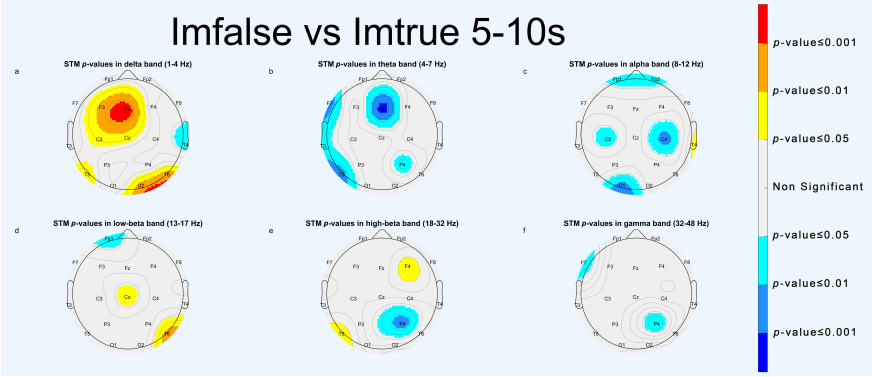


Figure 3.5: STMs of significant statistical activation of brain areas for "Imfalse vs. Imtrue" comparison (5–10 s). (a) delta band, (b) theta band, (c) alpha band, (d) low-beta band, (e) high-beta band, (f) gamma band.

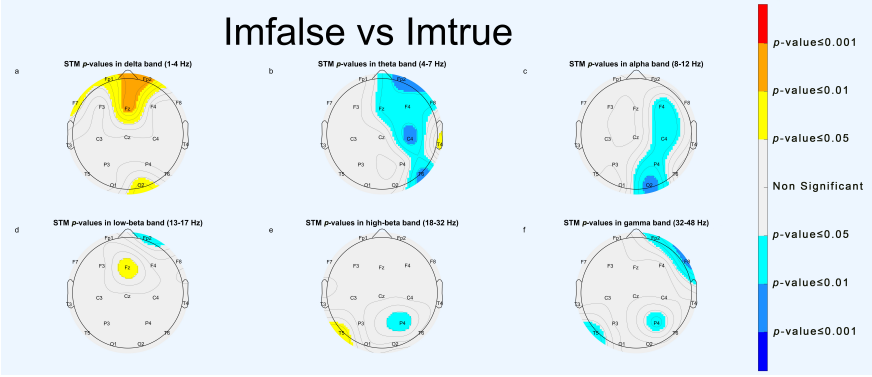


Figure 3.6: STMs of significant statistical activation of brain areas for "Imfalse vs. Imtrue" comparison (0–10 s). (a) delta band, (b) theta band, (c) alpha band, (d) low-beta band, (e) high-beta band, (f) gamma band.

Emotional Comparison As for the emotional comparison, the results of significant EEG activation are briefly reported in Figure 3.7 (0–10 s). For a complete overview of the results regarding emotional comparison, please refer to Figure A.2 and Figure A.3 in section A.1.

- In the "Happy vs. Neutral" comparison, greater significant activation was in the delta band in the frontal and occipital areas (Figure 3.7a, Figure A.2a and Figure A.3a) and in the alpha band in the left temporal and right parietal areas (Figure 3.7c and Figure A.3c) for faces expressing neutral emotions.
- In the "Happy vs. Sad" comparison, greater significant activities were in the theta band in pre-frontal and left occipital areas (Figure 3.7h and Figure A.3h) and in the low-beta band in the frontal and right occipital areas (Figure 3.7j and Figure A.3j) for faces expressing positive emotions, whereas there was greater significant activation in the alpha band in the left temporal area (Figure 3.7i and Figure A.2i) and in high-beta band in the right frontal area (Figure 3.7k and Figure A.2k) for faces expressing negative emotions. It is worth noting that in the first 5 seconds (Figure A.2g–l), faces expressing negative emotions elicited more significant activation, whereas in the last 5 s of the epoch (Figure A.3g–l), faces expressing positive emotion were predominant in determining statistical significance.
- In the "Neutral vs. Sad" comparison, significant activations in the low-beta band were found in the right occipital and left temporal areas (Figure 3.7p, Figure A.2p and Figure A.3p) for faces expressing neutral emotions.

ERP Analysis

ERP analysis was performed considering four areas of the cerebral cortex: LF, RF, LTO, and RTO. This was due to the different roles which these areas serve in face processing (LTO and RTO, as reported by Barton [36]) and decision making (LF and RF, as reported by Collins et al. [92]).

Originality Comparisons Statistical analysis on ERP components for originality comparison provided the following results (Table 3.3 and Figure 3.8).

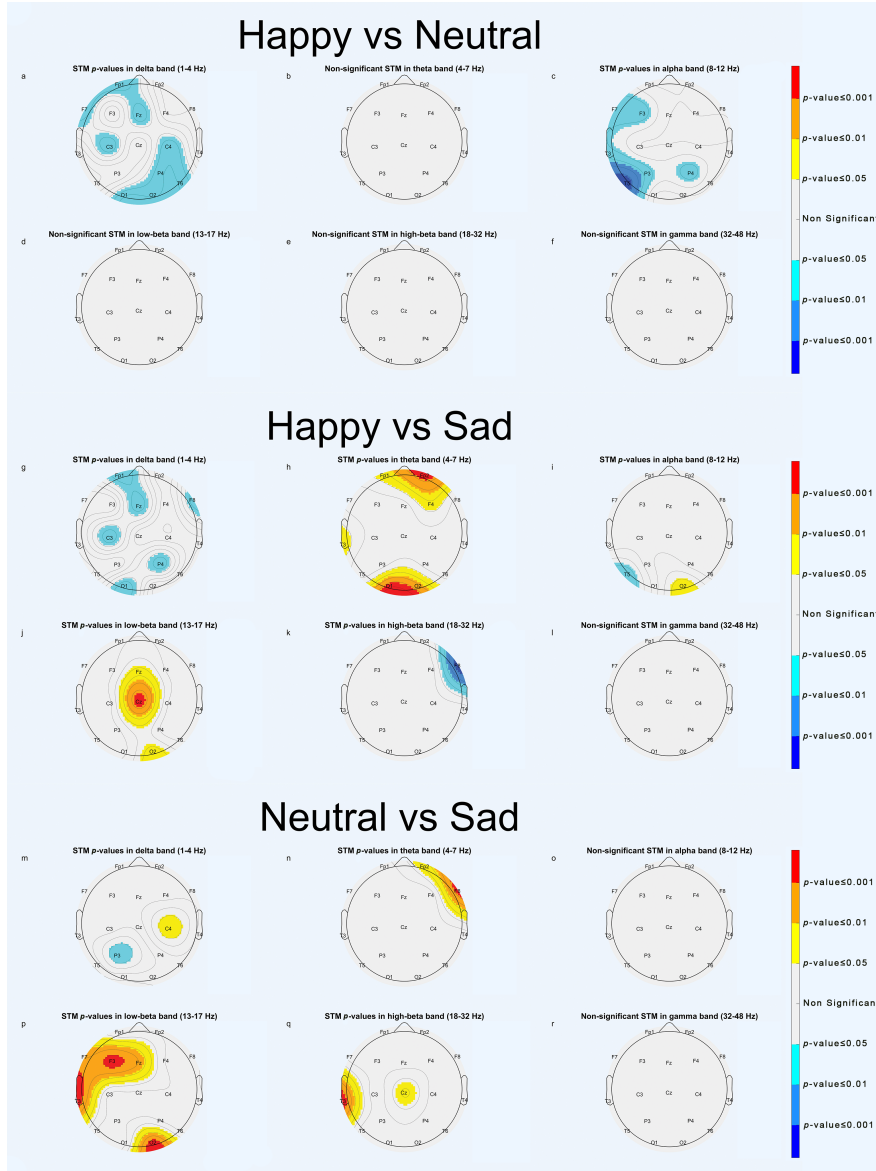


Figure 3.7: STMs of significant statistical activation of brain areas in emotional comparisons (0–10 s). "Happy vs. Neutral" comparison (a–f): (a) delta band, (b) theta band, (c) alpha band, (d) low-beta band, (e) high-beta band, (f) gamma band. "Happy vs. Sad" comparison (g–l): (g) delta band, (h) theta band, (i) alpha band, (j) low-beta band, (k) high-beta band, (l) gamma band. "Neutral vs. Sad" comparison (m–r): (m) delta band, (n) theta band, (o) alpha band, (p) low-beta band, (q) high-beta band, (r) gamma band.

Table 3.3: Statistical analysis results on ERP components total area and latency in originality comparisons (deepfakes vs. real faces). Prevalence is reported in brackets; "F" stands for false and "T" for true.

Comparisons	LF	RF	LTO	RTO
Imfalse vs. Imtrue	P300 (T) ↑	N250 (T) ←	N250 (T) ←	-
HappyF vs. HappyT	N100 (F) ←	-	P300 (T) ↑	-
NeutralF vs. NeutralT	-	-	-	N170 (F) ←
SadF vs. SadT	N250 (T) ←	-	P100 (F) ↑	-

↑ = significance in total area, ← = significance in latency.

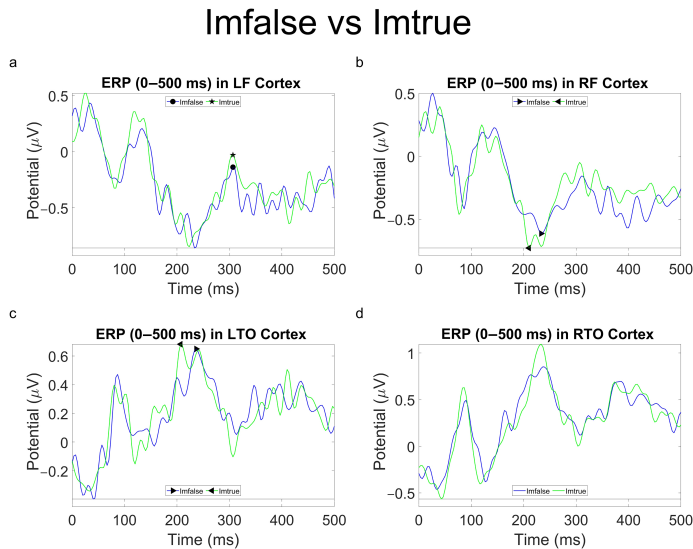


Figure 3.8: ERP (0–500 ms) in LF (a), RF (b), LTO (c), and RTO (d) areas for "Imfalse vs. Imtrue" comparison. Significant p -values ($p < 0.05$) for total areas are reported with the ★ (indicating prevalence) and ● symbols, whereas for latency, they are reported with the ◀ (indicating prevalence) and ▶ symbols.

Emotional Comparison As for the statistical analysis on ERP components for emotional comparisons, this produced the following results (Table 3.4).

Table 3.4: Results of statistical analysis on ERP components total area and latency for emotional comparisons (multiple comparisons between happy, neutral, and sad faces). Prevalence is reported in brackets; "H" stands for happy, "N" for neutral, and "S" for sad.

Comparisons	LF	RTO
Happy vs. Neutral	-	P100 (H) ↑
Happy vs. Sad	-	P100 (H) ↑
Imfalse_N vs. Imfalse_S	N100 (N) ↑	-
Imtrue_N vs. Imtrue_S	N170 (S) ↑	-

↑ = significance in total area.

3.1.4 Discussion

This study aimed to investigate how people could distinguish between real and AI-generated faces emphasizing emotional expressions and comprehend the effects of deepfakes on human perception and the possible difficulties they present in differentiating between real and artificial visual stimuli. To this purpose, statistical analyses of EEG correlates in terms of PSD- and ERP-related features were performed.

On the behavioral level, a good deepfake discrimination capacity was found, which confirmed studies on the recognition of AI-generated faces [147, 202, 236, 283]. Participants had good performance in recognizing the true faces as well [371, 450]. A good degree ($\sim 76\%$) of accuracy in classifying faces was observed, as reported in Table 3.1 and Table 3.2. Participants were slightly better at discriminating images with neutral emotional content than images with positive or negative emotional content. It seems to confirm the work of Montagrin et al., which highlighted the important role played by memory in facilitating the recognition of neutral faces in goal-relevant situations [313]. Statistical analysis of PSD-related features highlighted two main significant turn-ons for deepfakes: delta activation in the frontal (Figure 3.5a and Figure 3.6a) and right occipital (Figure 3.4a, Figure 3.5a and Figure 3.6a) areas could be due to a dynamic switching attention mechanism [214], meaning that participants spent more time interpreting synthetic

faces, whereas high-beta activation in the left temporal area, which includes the FG [118], states that FFA activation is not determined by the originality label of the face presented.

Theta activations in real faces were observed in the right frontal area (Figure 3.4b, Figure 3.5b and Figure 3.6b), according to Canales et al. [67], it indicated an increase in short-range frontal theta synchronization associated with visual imagery of faces and also with the need for cognitive control [73]. Theta, alpha, high-beta and gamma significant activities for real faces were all over the right hemisphere (RH), as shown in Figure 3.4b,c,e,f, Figure 3.5b,c,e,f, and Figure 3.6b,c,e,f, might instead hint a distinct pathway in the brain to discriminate real faces from synthetic ones, which is in line with findings by Sergent et al., suggesting a right hemisphere predominance for real faces when compared to objects [392]. Similar neural patterns have previously been linked to increased left visual field (LVF) activity during FR tasks [56].

Findings in the emotional comparison showed that it was feasible to discriminate between positive, negative, and neutral emotions. Results of frontal theta activation for happy faces (Figure 3.7h), especially in the second part of the epoch (Figure A.3h), were consistent with findings by Knyazev et al. reporting higher sensitivity to happy faces than to angry ones in the late, conscious FP stage [232]. Moreover, other statistical outcomes – reported in the section A.1 in Figure A.2g–l and Figure A.3g–l – showed how brain activation drastically changed between the first and the latter 5 seconds of the epoch in the "Happy vs. Sad" comparison more than any other.

Current ERP research findings have shown interesting results in FR processing. Specifically, fearful facial expressions have been found to produce a more pronounced negative N100 component than happy and neutral faces [278]. In contrast, the P100 component has shown to be sensitive mainly to domain-general visual processes and can be considered as a marker of individual face recognition [116] or, at least, of category-level face processing [121, 199]. The N170 component has been proved to be face-specific with respect to most objects, and increasing its latency when the structure of a face is hard to perceive [399]; the N250 component is, instead, thought to be generated in or near the FFA: it increases if a face image is the same as an immediately preceding face as compared with when it is different [399]. Finally, research on the early P300 has hinted that such components may reflect categorization and attention to motivational, relevant information,

including emotion, gender, or identity [20]. The results on the ERP statistical analysis, while not finding evidence in the literature, still suggested that brain activity might process AI-generated and real faces differently. In fact, in the comparison "Imfalse vs. Imtrue" (Table 3.3), the N250 component presented lower latencies for real faces both in the RF and LTO areas (Figure 3.8b,c), whereas earlier components seemed to be modulated, both in total area (P100) and latency (N100, N170), by deepfakes (Table 3.3). As for emotional comparison, an increase in the total area of the P100 component in RTO for happy faces compared to neutral and sad ones (Table 3.4, Figure 3.9 and Figure 3.10) was found consistently. In contrast, the "Neutral vs. Sad" comparison did not produce any significant outcomes until the split in deepfakes (N100 total area increased in the neutral class) and real (N170 total area increased in the sad class) faces.

During preliminary analysis, no significant difference in the outcomes of the labeling task between female and male participants before the pre-processing phase was reported. Significance was found solely on the labeling outcomes of the remaining epochs after pre-processing for the "sad_tf" labeled faces (p -value = 0.0346), with female participants being more inclined to classify as "synthetic" a real face expressing negative emotion. Moreover, considering the small sample size, gender differences for power spectrum and ERP analyses were not investigated.

The present study contributes to the deepfake perception, FP, and emotional engagement literature. The main point was the interplay of cognitive and emotional processes. Engaging these two sides helped in building a solid starting point for future research and further analysis involving different emotional and cognitive tasks. Similar studies could investigate behavioral and neurophysiological correlates in fragile subjects, such as older adults or persons with psychological diseases, to better understand distinct patterns in their neurophysiological response, aiming to provide an early evaluation of healthy elderly cognitive status. Future studies might also explore how one's affect influences the judgment on emotional content about external context. Recent research shows that some emotions can diminish, for example, deceit [58,154]. It is worthwhile noting that the proposed study presents some limitations. The first regards the small sample size of the involved subjects, which also precluded a gender difference investigation. Another limitation is the pre-processing pipeline, which can lead to different outcomes. Other EEG pre-processing pipelines, such as PREP [46] and APP [102], should be

Happy vs Neutral

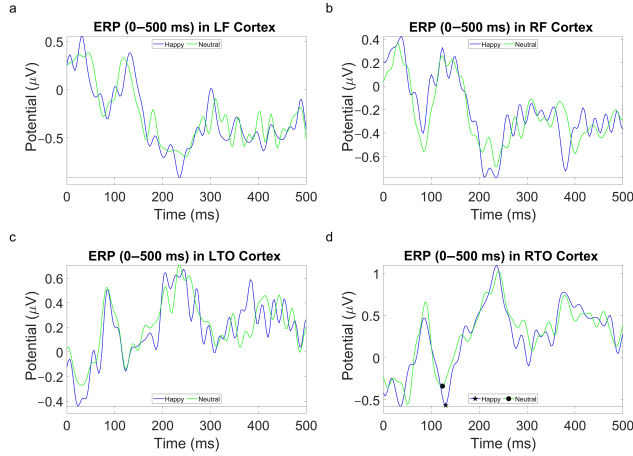


Figure 3.9: ERP (0–500 ms) in LF (a), RF (b), LTO (c), and RTO (d) areas for "Happy vs. Neutral" comparison. Significant p -values ($p < 0.05$) for total area are reported with the ★ (indicating prevalence) and ● symbols.

Happy vs Sad

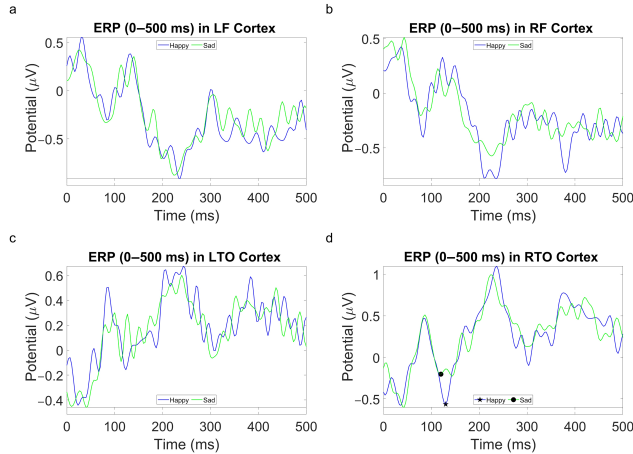


Figure 3.10: ERP (0–500 ms) in LF (a), RF (b), LTO (c), and RTO (d) areas for "Happy vs. Sad" comparison. Significant p -values ($p < 0.05$) for total area are reported with the ★ (indicating prevalence) and ● symbols.

investigated in future works for results robustness and repeatability assessment. Finally, FP dynamic investigation is an open question that deserves an appropriate deepening, since integrating cognitive and emotional brain processes activates complex brain responses regarding behavior and interaction among brain areas and networks. The future directions include increasing the number of participants to achieve more robust and accurate outcomes, as well as using self-report questionnaires from participants to pair a possible recognition strategy adopted by participants during the experiment with the results of the EEG analysis. Moreover, it could enable the application of more sophisticated modeling methodologies to gain deeper insights into cognitive and emotional engagement in perceiving and discriminating between real and synthetic faces.

3.2 Multimodal Neurophysiological Correlates of Word and Pseudoword Processing

3.2.1 Introduction

Speech and language disorders (SLDs) constitute one of the most prevalent developmental conditions, representing a major clinical and societal challenge. Recent epidemiological data estimate a prevalence of up to 12% in the general population [444], and approximately 8.3% among US children aged 3–17 years who experienced a speech or language disorder lasting at least one week during the previous year [330]. SLDs broadly include speech disorders, characterized by impairments in the articulation of sounds or fluency, and language disorders, defined as deficits in the comprehension or production of spoken, written or symbolic communication [444]. These difficulties typically emerge early in development, often around the second year of life, when affected children show delays in expressive vocabulary acquisition and reduced verbal output compared to typically developing peers, even in the absence of sensory deficits or other concurrent developmental conditions [84]. From a clinical perspective, the timely identification of SLD is essential, as these disorders may co-occur with neurodevelopmental disorders (NDDs) including autism spectrum disorder or emotional and behavioral difficulties [444]. Early diagnosis thus enables interventions before broader cognitive, academic and socio-emotional abilities become compromised. Despite their importance, the underlying neurobiological bases of SLD remain

only partially understood. Neuroimaging and neurophysiological studies frequently focus on cortical regions critical for linguistic processing. The Broca area (BA), located in the dominant frontal lobe near the motor cortex, is implicated in phonological planning and the integration of frontal, temporal and motor representations prior to speech execution [152]. Conversely, the Wernicke area (WA), in the posterior superior temporal gyrus near auditory and parietal cortices, contributes to the comprehension of spoken and written language. Understanding how these regions interact during controlled linguistic tasks can provide valuable insights into the mechanisms underlying speech and language development. A wide variety of clinical instruments is used for screening and diagnosing SLD, including questionnaires and structured test batteries [126, 375, 376, 444]. Among the most informative behavioral tools are pseudoword (PW) repetition and words-pseudowords aloud reading (WPWAR) tasks. PWs are pronounceable, meaningful-sounding stimuli constructed to follow the phonotactic and prosodic rules of real words while remaining unfamiliar to participants. Their controlled structure allows clinicians and researchers to examine phonological processing, short-term memory and articulatory planning while minimizing the influence of semantic knowledge. PW repetition and WPWAR have proven to be reliable and sensitive markers of linguistic impairments, successfully employed to detect deficits and to monitor rehabilitation outcomes in children with dyslexia or other language-related disorders [39, 94]. Additionally, PW-based tasks appear informative across the lifespan: evidence from older adults indicates that morphological complexity modulates performance depending on individuals' cognitive reserve, suggesting that PW processing remains tightly linked to cognitive resources even in aging [255]. Traditionally, the evaluation of PW and WPWAR performance has relied on qualitative assessments, wherein speech-language pathologists listen to utterances, identify articulatory errors, note pauses or omissions, and assign clinical scores. However, recent research has highlighted the importance of complementing qualitative scoring with objective physiological and acoustic measurements, which can provide finer-grained insights into speech production mechanisms. Acoustic analyses allow the quantification of vocal features and the identification of subtle alterations in prosody, articulation or phonation associated with different linguistic loads or cognitive states [19, 184]. These measures may reveal discomfort, effort or compensatory strategies that are difficult to capture through auditory inspection alone. Beyond the acoustic domain, EEG

provides high-temporal resolution insights into the neural processes underlying speech and language tasks. Among EEG-derived measures, ERPs such as the N400 are particularly relevant. The N400 is a centro-parietal negativity peaking around 400 ms, associated with lexical-semantic processing [242]. Both words and pseudowords elicit N400 activity, reflecting phonological and semantic integration demands [148]. In addition to ERPs, oscillatory features derived from PSD analyses can reveal how cortical rhythms support speech perception and production, including engagement of theta, alpha and beta bands during phonological processing, working memory and articulatory planning. Complementary to brain signals, peripheral physiological signals such as EDA offer an additional window onto the ANS, particularly the sympathetic branch. EDA amplitude and dynamics reflect changes in arousal and cognitive effort, and have been previously used to investigate speech-related phenomena. For instance, Walsh and Usler [445] examined EDA in preschool children to assess awareness of stuttering, and Marzi et al. [292] reported significant EDA modulation during affective word reading tasks. Nevertheless, despite growing evidence linking arousal and speech production, no published studies have directly investigated whether and how PW-based repetition tasks modulate EDA responses, nor whether EDA and acoustic markers interact during controlled linguistic processing. These considerations highlight the potential value of a multimodal approach to investigating the cognitive and physiological correlates of speech and language tasks. While prior studies have examined EEG correlates of linguistic processing, and others have assessed autonomic or acoustic markers in speech-related contexts, no framework has combined central (EEG), peripheral (EDA) and acoustic measures within the same WPWAR task paradigm.

The aim of this study is therefore to characterize, in healthy adult participants, the multimodal physiological signatures elicited during a WPWAR task that mirrors those routinely used in clinical and logopedic practice. Specifically, this work integrates (i) EEG measures, including N400 event-related potentials and power spectral density features; (ii) EDA measures and voice parameters, respectively capturing sympathetic arousal and describing voice quality and speech production characteristics, during utterances of words and PWs with varying syllabic complexity. By jointly analyzing these complementary dimensions, the present work seeks to evaluate the robustness of the WPWAR paradigm and to explore potential associations between neural, autonomic and acoustic responses. This multimodal characterization

represents a foundational step for future applications in clinical populations, where such integrative measures could improve the detection, monitoring and understanding of speech and language disorders.

3.2.2 Experimental set-up

A total of 55 healthy volunteers, all Italian native speakers, were recruited for this study to perform WPWAR. Although all 55 volunteers completed the same experimental protocol, the number of participants included in the analyses varied depending on the quality and usability of the physiological signals. Specifically, 44 participants (27 F and 17 M), aged between 20 and 29 (22.1 ± 2.1 y.o.), provided EEG recordings of sufficient quality for the analysis of ERPs and PSD features, whereas 45 participants (27 F and 18 M), aged between 20 and 29 (22.4 ± 2.1 y.o.), provided EDA and voice recordings that met the criteria for autonomic and acoustic analysis.

This study was approved by the Institutional Review Board (endorsement of compliance with the Opinion of the Ethics Committee for Research no. 275 of 04/09/2023), and all participants gave written informed consent. Volunteers were set on a chair in front of a monitor where W and PW were presented. EEG acquisition was carried out by using the DSI-24 helmet (Wearable Sensing, San Diego, CA, USA). The helmet was wirelessly coupled with the Trigger Hub device (Wearable Sensing, San Diego, CA, USA) to associate the neurophysiological recording at specific time-relevant events. A Shure SM58 (Shure Inc., Niles, IL, USA) microphone was used for speech recordings to ensure that response times could not produce artifacts related to movements in the N400 component time window and a dedicated DSI-24 external module was used to record EDA. Sampling frequency was set at $f_s = 300\text{Hz}$ for EEG and EDA signals and at $f_s = 44.1\text{kHz}$ for voice recordings (see section 2.8).

After a 180 s baseline period, the experiment started and it was divided into three sections:

1. subjects completed a counting number task, read a standardized sentence and uttered three sustained cardinal vowels ($/a/$, $/i/$, $/u/$), following the guidelines of the Società Italiana di Fonologia e Logopedia [359].
2. subjects read 15 words.

3. subjects read 15 PWs.

An optical sensor-based triggering system was used to track sections and transitions between stimuli.

For the latter two sections of the experiment, five Italian words (Ws) and five PWs of 2-, 3- and 4- syllables each were selected from the test battery developed by Dispaldro et al. [127], for a total of 30 elements. The entire dataset provided by Dispaldro et al. [127] was not used to reduce the negative impact that instrumentation and experiment duration might have on fatigue and stress. Instead of repeating listened PW [126], subjects read stimuli from a monitor and then uttered them without time limits or correction from experimenters [39, 94]. In this way, the role of phonological short-term memory, activated in the PWR task, was reduced. Ws and PWs were therefore visually presented to each participant as black font computer text strings (TS), over a grey background on the monitor and separated into two blocks of 15 TS each. Ws were presented before PWs, and every block was structured to show 5 per 2-syllables TS first, 5 per 3-syllables TS then and 5 per 4-syllables TS at last (Figure 3.11). Presentation order of Ws and PWs of the same syllable length within trials was randomized [7] and participants faced 3 seconds of rest before dealing with the next stimulus. A motion artifact and three testing utterances were used to synchronize EEG and EDA acquisition with voice recordings.

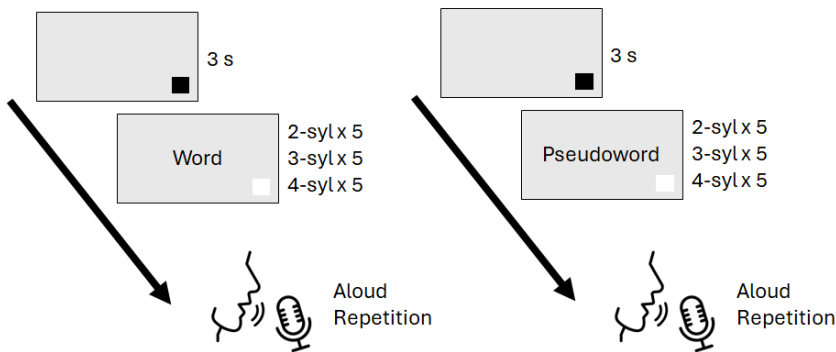


Figure 3.11: WPMAR experimental protocol timeline.

3.2.3 EEG Analyses

Continuous EEG data were pre-processed in MATLAB 2023a with EEGLAB [120] by using the HAPPE framework [164], as previously described in subsection 2.3.1 (band-pass filtering 1–45 Hz). After the HAPPE pre-processing, EEG signals were epoched into individual trials from -1 to 2 s relative to stimulus onsets. A total of 1219 epochs were retained for further analysis (Table 3.5), while 101 epochs were not further inspected after the EEG pre-processing step of rejection.

Table 3.5: Epochs division according to stimuli type after EEG pre-processing.

TS / syllables no.	2	3	4	total	percentage
W	205	202	197	604	49.6%
PW	207	208	200	615	50.4%
total	412	410	397	1219	100%
percentage	33.8%	33.6%	32.6%	100%	

For each epoch, the average power spectrum in low-beta (13–17 Hz), high-beta (18–32 Hz) and gamma (32–48 Hz) for all channels and the ERPs for 4 specific brain regions were computed. PSD for each channel in each of the 3 bands of analysis was computed as described in subsection 2.3.3, while for ERPs baseline correction was performed by subtracting the EEG average in the -250 to 0 ms time window. Brain regions considered in ERP analysis were left prefrontal cortex (LPFC), comprising Fp1, F3 and F7 channels; the left temporal cortex (LTC), comprising T3 and T5 channels; the right prefrontal cortex (RPFC), comprising Fp2, F4 and F8 channels; and right temporal cortex (RTC), comprising T4 and T6 channels.

Statistical Analysis Statistical analysis was performed on both the latency and amplitude of the N400 component for canonical ERP analysis. Latency was computed with the fractional area method [277] and amplitude measures were computed as the total area in the 200–600 ms time window, as previously described in chapter 2, section 2.3, subsection 2.3.2. PSD time-frequency EEG extracted feature was the average in the 200–600 ms time window for each band of analysis and values were then z-scored across the

scalp to take into consideration subject variability. Since all considered EEG features were not normally distributed, according to the Shapiro-Wilk test (significance level $p \leq 0.05$), the non-parametric Wilcoxon signed rank test (significance level $p \leq 0.05$) was used for statistical analysis of the following comparisons:

- PWs vs. Ws (all 15 TS);
- PWs vs. Ws (only for 2-syllables TS);
- PWs vs. Ws (only for 3-syllables TS);
- PWs vs. Ws (only for 4-syllables TS).

Results

PSD results (Figure 3.12) are reported in the form of STMs. Also, FCSTMs were used to simplify visualisation, highlighting the statistically significant areas ($p \leq 0.05$, $p \leq 0.01$, $p \leq 0.001$). If a region of the FCSTM assumes warm colors, it means that activation for PW is statistically greater than W; on the contrary, if the area assumes cold colors, the activation for W is statistically greater than PW. Results of statistical analysis on N400 magnitude and latency between PW and W are presented in Figure 3.13–Figure 3.16, reporting ERP along with its confidence intervals.

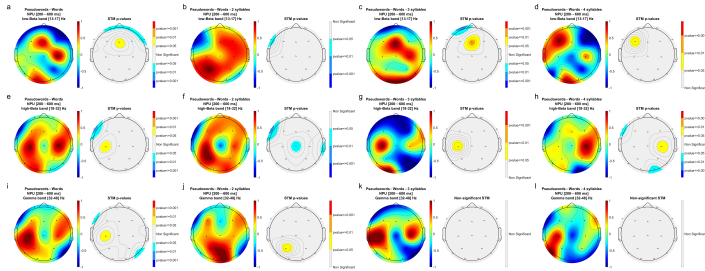


Figure 3.12: STM and FCSTM representing PW–W PSD rescaled values and significant p -values towards PW (warm colors) and W (cold colors) computed over the N400 component time window 200–600 ms in low-beta (a,b,c,d), high-beta (e,f,g,h) and gamma bands (i,j,k,l) considering all (a,e,i), only 2-syllables (b,f,j), only 3-syllables (c,g,k) and only 4-syllables stimuli (d,h,l).

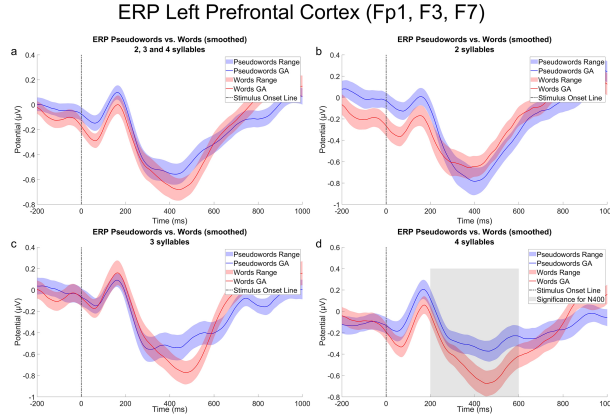


Figure 3.13: Smoothed ERP waveform in -200 – 1000 ms time window for LPFC when comparing PW (blue) with W (red) considering all (a), only 2-syllables (b), only 3-syllables (c) and only 4-syllables stimuli (d). Significant p-values ($p \leq 0.05$) for larger N400 components are reported with a grey rectangle over the 200 – 600 ms time window.

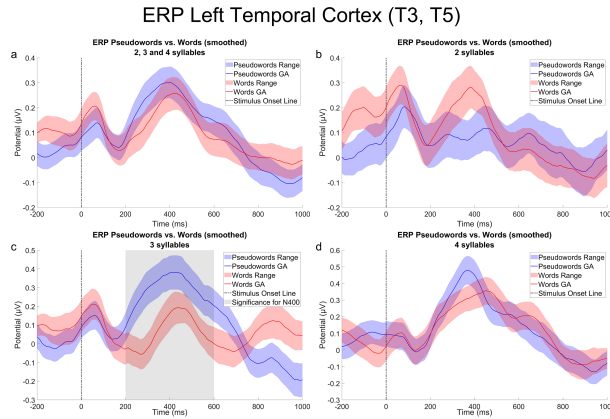


Figure 3.14: Smoothed ERP waveform in -200 – 1000 ms time window for LTC area when comparing PW (blue) with W (red) considering all (a), only 2-syllables (b), only 3-syllables (c) and only 4-syllables stimuli (d). Significant p-values ($p \leq 0.05$) for larger N400 components are reported with a grey rectangle over the 200 – 600 ms time window.

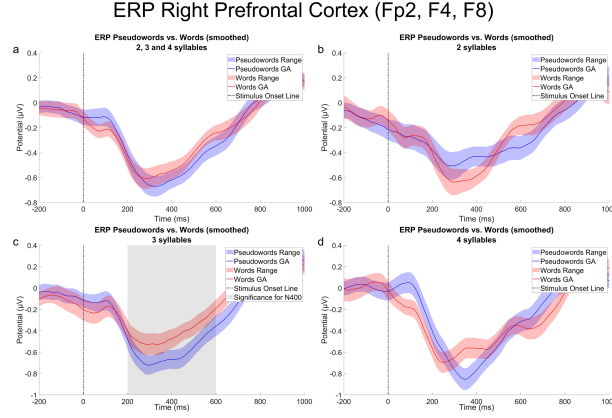


Figure 3.15: Smoothed ERP waveform in -200 – 1000 ms time window for RPFPC when comparing PW (blue) with W (red) considering all (a), only 2-syllables (b), only 3-syllables (c) and only 4-syllables stimuli (d). Significant p-values ($p \leq 0.05$) for larger N400 components are reported with a grey rectangle over the 200 – 600 ms time window.

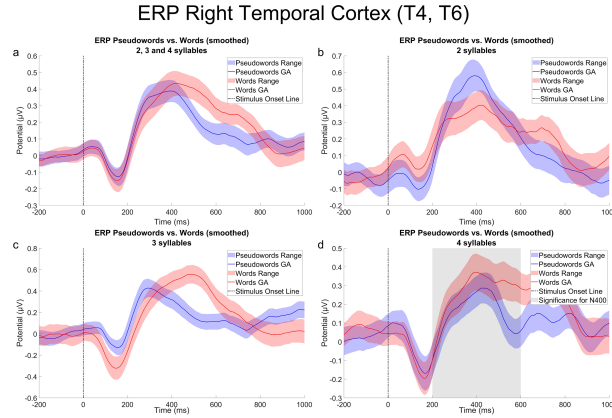


Figure 3.16: Smoothed ERP waveform in -200 – 1000 ms time window for RTC area when comparing PW (blue) with W (red) considering all (a), only 2-syllables (b), only 3-syllables (c) and only 4-syllables stimuli (d). Significant p-values ($p \leq 0.05$) for larger N400 components are reported with a grey rectangle over the 200 – 600 ms time window.

Discussions

This work analyzed EEG correlates, nominally the N400 ERP component and channel-PSD, in healthy volunteers who performed a WPWAR task with TS of different syllable lengths. The aim was to verify if there were differences at the neurophysiological level concerning four brain regions involved in articulation and understanding of language and speech. While no difference emerged for latency values, larger N400 components were found for 4-syllables W both in LPFC (Figure 3.13d, $p = 0.0073$) and in RTC (Figure 3.16d, $p = 0.0309$). These results are in agreement both with the semantic working memory capacity of the LPFC, which is invoked more for semantic than nonsemantic analysis [165], and the found enhanced positivity of the N400 over the RTC for the congruent condition in a semantic anomaly task [158]. Interestingly, a recent study conducted on adolescents with autism spectrum disorder (ASD) [461] highlighted a delayed N400m onset latency over the LPFC in low-functioning ASD adolescents when compared to high-functioning ones and the typically developing group. This finding is consistent with impaired lexico-semantic processing and deficient cognitive control. Gabrieli et al. [165] also pointed out that the duration of stimulus presentation could influence the magnitude of the N400 component in the LPFC. On the contrary, PW elicited larger N400 for 3-syllables stimuli in both LTC (Figure 3.14c, $p = 0.0011$) and RPFC (Figure 3.15c, $p = 0.0258$). Evidence in the literature highlights that not only has the LTC been thought to be a good candidate source for the N400 to semantic incongruity [158], but also the RPFC has been found to be needed to resolve the so-called "deep incongruity", by contributing to discover divergent, alternative word meanings that are based on weak semantic associations [288]. These findings align with outcomes of PSD statistical analysis reported in Figure 3.12: in low-beta, high-beta and gamma bands a dichotomic behavior of opposite prefrontal and temporal cortices can be observed, highlighting two different pathways for W (RTC and LPFC) and PW (LTC and RPFC) processing over the N400 component time window. Even with a limited control group of young and neurotypical subjects, EEG correlates can be utilized to describe brain processes related to speech and language, as shown by the proposed study.

3.2.4 EDA and Voice Analysis

EDA Analysis

EDA signals were preprocessed with a low-pass FIR filter of order 500, with cut-off frequency 5 Hz and z-scored. The cvxEDA algorithm [176] was then applied for tonic (SCL) and phasic (SCR) component separation, as previously described in subsection 2.4.2. Features extraction was based on [29]: PS MSymp (SC mean spectral power in the 0.045-0.25Hz band), SCL Mean, SCL Std, SCR Peak (max peak amplitude in SCR), SCR N (number of SCR peaks), SCR AmpSum (SCR peaks amplitude sum), Lat2 (latency between stimulus and peak). Moreover, Phasic and Tonic Sample Entropy (SE), and CompEDA [323] were included (for a complete overview of the features, please refer to section 2.4). These parameters were calculated both considering the whole duration of each task and single stimuli.

Acoustical Analysis

Triggering signal and MATLAB function detectSpeech.m were concurrently used to automatically segment audio files. Each utterance was processed with the open-source software BioVoice [315] giving 34 acoustical parameters concerning both frequency domain, such as fundamental frequency F0, formants and jitter, and time domain, such as voiced duration, pause duration, voiced/unvoiced percentage. According to [445] six more parameters were computed: amplitude envelope (AmpEnv), root-mean square (RMS) and zero crossing rate (ZCR), spectral roll-off, spectral bandwidth and spectral centroid. All 40 parameters were computed separately for female (F) and male (M) groups to account for physiological differences between genders.

Statistical Analysis The first aim of this work was to evaluate whether EDA features only can discriminate between baseline, W and PW tasks. A Kruskal-Wallis test was performed on EDA metrics computed on the whole duration of the three tasks, both for tonic and phasic component. Pair-wise differences were investigated by applying Bonferroni post-hoc correction. The remaining EDA features have been evaluated between W and PW tasks by means of a Mann-Whitney test. Level of significance was set at 0.05 for both tests. Pearson correlation analysis between acoustical and EDA features was performed to understand whether SNS activation, expressed by EDA features, induces concurrent vocal properties alterations. Overall, 430

comparisons were investigated between each EDA and acoustical feature. The level of significance was 0.01. Correlations were calculated separately for the F and M cohorts.

Results

Table 3.6 shows the results of statistical analysis for EDA features computed for baseline, W and PW. Table 3.7 shows statistical results related to EDA features in the WPGAR tasks.

Table 3.6: Statistical results for EDA analysis, considering features available for all the conditions. (*), (#) and (+) denote significant differences between baseline and W, baseline and PW, W and PW, respectively. The Bonferroni post-hoc correction was applied (Kruskal-Wallis test, level of significance 0.05). Median and interquartile range (iqr) values are reported for each condition.

EDA feature	Baseline	Task	
		W	PW
PS MSymp* ⁺	0.89 (0.16)	0.48 (0.18)	0.96 (0.45)
SCL Mean* ^{#+}	-0.44 (0.22)	0.21 (0.26)	0.72 (0.33)
SCL Std* ^{#+}	0.90 (0.15)	0.58 (0.21)	0.24 (0.22)
CompEDA ^{#+}	0.14 (0.15)	0.10 (0.12)	0.29 (0.16)
SE Phasic* [#]	0.04 (0.04)	0.08 (0.07)	0.10 (0.09)
SE Tonic* ^{#+}	0.006 (0.005)	0.009 (0.006)	0.019 (0.014)

Concerning the correlation analysis between acoustical and EDA features, Table 3.8 reports Pearson’s ρ coefficient and the p-value for the W and the PW tasks, limited to four syllables stimuli. Only the significant correlations in common between M and F are reported.

Figure 3.17 shows the scatter plot for CompEDA and RMS for M (observations are denoted by ‘X’) and F (‘o’) groups, as well as their respective regression lines (solid and dashed for M and F cohorts, respectively).

Discussions

This work reported a preliminary analysis of physiological signals acquired during W and PW tasks. The aim was assessing possible physiological

Table 3.7: Statistical results for EDA analysis, considering features available only for the W and PW tasks. (+) denotes a statistical difference between W and PW (Mann-Whitney test, level of significance 0.05). Median and interquartile range (iqr) values are reported for each condition.

EDA feature	Task	
	W	PW
SCR peak ⁺	1.13 (1.02)	0.76 (0.82)
SCR N ⁺	84 (29)	56 (21)
SCR AmpSum ⁺	28.2 (29.0)	14.7 (11.3)
Lat2	45.1 (59.8)	37.3 (94.2)

Table 3.8: Correlation results between EDA and acoustical parameters. Level of significance 0.01.

W				
Correlation	F		M	
	ρ	p-value	ρ	p-value
$SCR_N - F0_{median}$	0.24	0.003	-0.37	E-4
$SE_{Tonic} - ZCR$	-0.24	0.004	-0.27	0.008
PW				
Correlation	F		M	
	ρ	p-value	ρ	p-value
$CompEDA - RMS$	-0.23	0.006	0.37	E-4
$SCR_N - F0_{median}$	0.22	0.007	-0.36	E-4
$CompEDA - AmpEnv$	-0.24	0.004	0.29	0.004

changes during PW reading that can be detected by EDA and speech analysis. Firstly, it was evaluated if EDA features were able to discriminate between tasks and baseline. EDA features related to the tonic component (e.g., SCL Mean, SCL Std) allowed a pairwise discrimination between the three tasks. Significant differences were obtained as well on EDA phasic component features. For instance, SE phasic or SCR peak allowed discrimi-

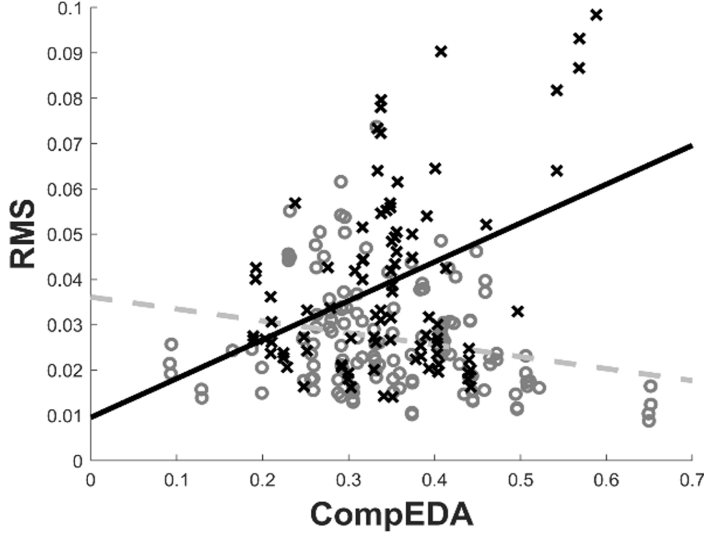


Figure 3.17: Scatter plot between CompEDA and RMS for M (X) and F (o) groups.

nating between W and PW tasks. Furthermore, the PW task had the highest entropy values for the phasic component (SE Phasic) as compared to the W task and the baseline (Table 3.6). The M cohort presented a negative correlation on F0 median ($\rho=-0.37$, p-value $e-04$), while the F cohort showed a positive correlation for the same parameter ($\rho=0.24$, p-value 0.003). An alteration of F0 may be associated with discomfort, stress or cognitive workload [168, 445]. Giddens et al. [168] highlighted that both increases and decreases of F0 can be detected in response to such conditions. Table 3.8 shows that the correlation of F0 median with EDA feature was found significant both for the W and PW tasks: thus, this shift may be simply induced by experimental conditions regardless of the proposed tasks. Table 3.7 shows a relevant difference between W and PW tasks. Specifically, while EDA signal complexity increased during PW reading, which is expressed by CompEDA, opposite effects on RMS and AmpEnv acoustical features appeared, in line with [168]. These parameters represent good approximations of vocal intensity, therefore it seems that, when uttering PW, M tended to increase their loudness, whereas F decrease it (Figure 3.17). To assess if the considered features, as well as the administered tasks, could be sensitive to SLDs this

approach must be applied on a larger dataset and on pathological subjects. Also, future work should be devoted to account for various inter-physiological factors such as higher sensitivity to stress or stress unresponsiveness to this task. Nevertheless, results suggested that EDA and speech features may be used as an objective alternative to scoring methods in their assessment.

3.3 Conclusions

This chapter aimed to characterize basic psychophysiological responses to stimuli differing in familiarity, semantic content, or authenticity, under highly controlled experimental conditions. Through two paradigms addressing visual face perception and speech related lexical processing, the chapter mainly sought to establish a reference framework for how neural, autonomic, and behavioral systems respond to natural versus non-natural stimuli in the absence of strong contextual or social influences. EEG correlates of face perception revealed that real and AI generated faces, even when matched for emotional expressions, elicited partially distinct neural dynamics. Behavioral performance indicated a generally preserved ability to discriminate between authentic and synthetic faces, with subtle modulations related to emotional content. At the neurophysiological level, differences in spectral and event related activity suggested that authenticity evaluation involves not only perceptual mechanisms, but also higher order processes associated with attention, cognitive control, and emotional engagement. Although exploratory and limited by sample size, these findings support the relevance of temporally resolved neural markers in the study of deepfake perception and raise open questions regarding individual strategies and affective modulation. In the WPWAR task, W and PW produced differentiated responses at both cortical and peripheral levels. EEG analyses highlighted distinct engagement of prefrontal and temporal networks depending on semantic availability and syllabic structure, indicating that pseudoword reading imposes increased lexico phonological and cognitive control demands. These central effects were accompanied by systematic modulations of autonomic activity and vocal production, with electrodermal and acoustic features reflecting changes in sympathetic regulation and speech intensity. The convergence of these measures suggests that even simple reading tasks elicit coordinated adjustments across neural, autonomic, and behavioral systems in response to linguistic load. The findings presented in this chapter provide converging

evidence that contrasts between familiar or meaningful stimuli and their non-semantic or synthetic counterparts are reflected in coherent patterns across multiple physiological domains. At the same time, it should be noted that some of the spectral and complexity-based features considered in this chapter may be sensitive to preprocessing choices and parameter settings; the adoption of standardized preprocessing pipelines (see subsection 2.3.1 and subsection 2.4.2) was therefore intended to mitigate potential methodological biases and ensure consistency across analyses. By adopting a multimodal and analytically flexible approach, the chapter establishes a reference map of psychophysiological reactivity under constrained laboratory conditions. This foundation is instrumental for the subsequent chapters, where similar measurement principles and analytical strategies are extended to more complex, dynamic, and socially embedded experimental contexts, allowing deviations from these baseline patterns to be interpreted in a principled manner.

Chapter 4

Multimodal Cognitive and Affective Dynamics in Game-Based Tasks

This chapter explores psychophysiological engagement during interactive, goal-directed digital games, introducing game-based experimental paradigms as a controlled yet ecologically plausible context for investigating cognitive and emotional processes during active task performance. Two casual digital games were employed: a fast-paced visuomotor task (Snake game) and a memory-driven task (Matching Pairs game). Across three complementary studies, central, autonomic, affective, and behavioral signals were integrated to characterize how cognitive load, emotional activation, and performance-related dynamics unfold during gameplay. The first study examines EEG activity in an Italian cohort during the Snake game, focusing on spectral power modulation across different phases of gameplay and its relationship with task performance. This analysis aims to identify neural signatures associated with adaptive cognitive engagement and performance efficiency in a continuous visuomotor context. The second study investigates pupillary dynamics during the Matching Pairs game in a similar Italian cohort, leveraging pupillometry as an objective marker of autonomic arousal and cognitive resource allocation. Classical and nonlinear PD metrics are related to subjective affec-

tive reports and performance measures to assess their sensitivity to memory-related task demands. The third study adopts a multimodal and cross-cultural perspective, integrating FER and ECG-derived HRV in a large sample of Italian, Korean, and Japanese participants performing both games. FE patterns are analyzed both statically and dynamically using probabilistic and Markov-based approaches to capture cultural differences in emotional expression and regulation over time. These affective features are then combined with canonical and complex HRV metrics to examine how emotional dynamics and autonomic regulation jointly relate to cognitive performance across tasks and cultural contexts.

1

This chapter introduces a game-based experimental paradigm as the second empirical context of the present thesis, following the investigation of basic psychophysiological responses to controlled stimuli presented in the previous chapters. Here, the focus shifts toward interactive, goal-directed tasks implemented through simple digital games, which provide a structured yet ecologically plausible setting to examine cognitive, emotional, and autonomic processes during active engagement. Digital games offer a unique methodological advantage in experimental research: they combine well-defined rules, explicit performance outcomes, and continuous interaction, allowing the systematic investigation of how cognitive load, attention, and affective responses unfold over time. While such paradigms share conceptual similarities with serious-game frameworks, the tasks employed in this chapter are not designed as serious games per se. Instead, they are used as standardized experimental tasks that enable controlled manipulation of task demands and objective quantification of performance, while maintaining a level of engagement comparable to everyday digital interactions. The aim of this chapter is to characterize how psychophysiological signals reflect cognitive engagement and emotional activation during gameplay, and how these responses are modulated by task structure, performance, and individual or contextual factors. In line with the general objectives of the thesis, the chapter adopts a

¹The section 4.3 of this chapter has been published as “Pupil Dilation Dynamics in Serious Game Emotional Activation” in *IEEE Gaming, Entertainment, and Media Conference (GEM)*, vol. 2024, pp. 1–4, 2024 [65]. The section 4.4 of this chapter has been published as “Multimodal Analysis of Emotions in Gaming: Understanding Cultural Influences” in *IEEE Transaction of Affective Computing*, 2026 [182].

multimodal perspective, integrating central, peripheral, and behavioral measures to capture different facets of human response during interactive tasks. To this end, two casual digital games were employed: the Snake game, primarily characterized by continuous visuomotor coordination and increasing time pressure, and the Matching Pairs game, which places greater demands on memory, attention, and decision-making under time constraints. Three complementary studies, each targeting a specific aspect of psychophysiological engagement during gameplay, are presented. The first study focuses on central nervous system dynamics by examining EEG activity and subjective affective responses during the Snake game, with particular attention to temporal changes in neural oscillatory patterns as a function of cognitive load. The second study investigates pupil dynamics during the Matching Pairs game, leveraging pupillometry as a marker of autonomic arousal and cognitive effort, and relating objective pupil metrics to subjective affective reports and task performance. The third study adopts a fully multimodal and cross-cultural approach, integrating AI-based FE recognition data and HRV analysis to explore emotional and autonomic responses during both games across Italian, Korean, and Japanese participants, thereby addressing the role of cultural background in shaping emotional expression and physiological regulation.

Immediately following this introduction, the chapter presents a description of the experimental context. This section provides a common framework for all subsequent analyses and is intended to avoid redundancy across studies. The individual study sections then build upon this shared experimental foundation, focusing on modality-specific methods, analyses, and results.

4.1 Materials

4.1.1 Participants and Experimental Paradigm

A total of 129 healthy volunteers from three different cultural backgrounds participated in the proposed experimental protocol, comprising Italian, Korean and Japanese participants. All participants provided written informed consent prior to participation. The experimental protocol was approved by the Institutional Review Board, with endorsement of compliance from the Ethics Committee for Research (Opinion No. 275, dated April 9, 2023), and complied with national data protection regulations, including DL-101/2018

(Italy), the Personal Information Protection Act (PIPA, South Korea), and the Act on the Protection of Personal Information (APPI, Japan).

The experiment followed a detailed operational protocol that specified standardized procedures for the conduct of the study, and all sessions took place in similar laboratory-controlled environments. To maintain consistent visual and physiological recording conditions, ambient lighting was controlled by darkening the windows and keeping the ceiling lights continuously on throughout data collection. Participants were seated in an adjustable chair that was set to a fixed height, and their distance from the webcam was standardised using a marked position on the table to minimise variation in posture and upper-body orientation. They were instructed to maintain an upright seated position, keep their feet flat on the floor, and refrain from unnecessary body movements during the recording period. These measures were implemented to reduce variability in the physiological signals that might arise from differences in posture or gross bodily movement.

At the beginning of the experimental session, participants completed a demographic questionnaire. Subsequently, the recording systems were properly applied on the participants, who seated 50–70 cm from the monitor. After sensor placement, a 3-minute eyes-open resting-state baseline was recorded. Participants were then introduced to the experimental tasks through a demonstration round of both the Snake game and the Matching Pairs game, aimed at familiarizing them with the task mechanics and control devices. The demonstration trials were not included in the subsequent analyses. Following the demonstration phase, participants completed the PANAS to assess their baseline emotional state. They then performed three full trials of the Snake game. At the end of this block, PANAS was administered again to evaluate task-related affective changes. Participants subsequently completed three full trials of the Matching Pairs game. After the completion of the gaming tasks, a 1-minute resting-state final baseline was recorded. The experimental session concluded with a final administration of the PANAS questionnaire. Figure 4.1 provides a complete overview of the experimental procedure.

4.1.2 Physiological Recordings

Physiological setups and recordings differed across participant groups. Italian participants were recorded using a multimodal setup including EEG (DSI-24, Wearable Sensing, $f_s = 300Hz$), ECG (Shimmer Sensing, $f_s =$

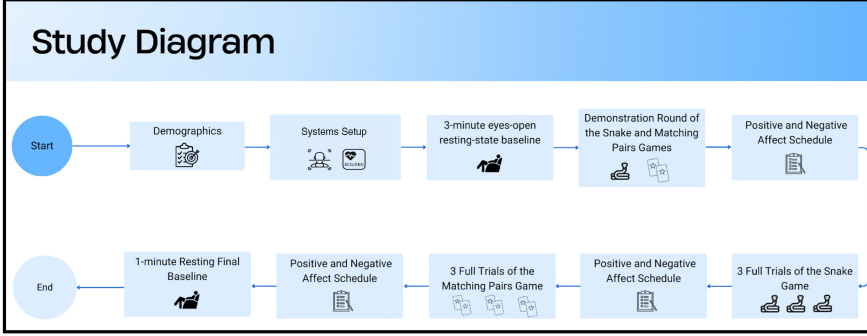


Figure 4.1: Overview of the proposed experimental paradigm.

300.62Hz), FE data via WAFER platform ($f_s = 1Hz$), and pupillometry ($f_s = 50Hz$) using Tobii Pro Glasses 3. Korean and Japanese participants were recorded using ECG (RUSA, $f_s = 250Hz$) and FE data via WAFER ($f_s = 1Hz$). All physiological signals were synchronized with gameplay events using dedicated triggering systems and logged timestamps, allowing accurate temporal alignment between game logs and physiological data. For a complete overview of the used systems, please refer to section 2.8.

4.1.3 Snake Game

The Snake game implemented for this study closely resembles the traditional version (Figure 4.2), where the primary objective is to consume as many items as possible. Unlike some variants, this version of the Snake game does not implement a countdown timer. Instead, gameplay concludes when the snake’s head makes perpendicular contact with either its own body or the boundaries of the playing area. To play the Snake game, participants used the keyboard arrow keys ($\uparrow$, $\downarrow$, $\leftarrow$, $\rightarrow$).

Snake Game Performance Score A dedicated scoring system for the Snake game was designed to reward both efficiency and precision, adjusting for the increasing difficulty as the snake lengthens during gameplay. The Snake game performance score (S_{GP}) was calculated using the snake’s initial pixel length ($L_0 = 5$) and the playing area in pixels ($PA = 400$), factoring in the number of items consumed (EI), as expressed in Equation 4.1:



Figure 4.2: Illustration of the Snake game, during gameplay and upon completion.

$$S_{GP} = \begin{cases} \sum_{k=1}^{EI} \left[\left(1 + \frac{k}{L_0}\right) - \frac{\Delta T_k}{PA} \right], & k > 0, \\ 0, & k = 0, \end{cases} \quad (4.1)$$

where ΔT_k is the time taken to consume each item. The Equation 4.1 reflects a balanced approach to scoring, emphasizing the player's ability to consume items efficiently and the adaptive challenge posed by the snake's increasing length.

4.1.4 Matching Pairs Game

The Matching Pairs (Figure 4.3) game implemented in this research is a modified version of the standard format. It includes six symbol pairs, totalling twelve symbols. The game starts a 35-second countdown when the participant starts to play. The game ends in two ways: either the countdown runs out, or the participant successfully matches all pairs of symbols. The symbols used in the game are designed to be easily distinguishable by shape and colour, which helps to reduce confusion and increase attention. The position of the symbols is randomized after each round of the game to

ensure variability and maintain the game’s challenge. It is played by means of a mouse and its left button to select card pairs.



Figure 4.3: Illustration of the Matching Pairs game, before start and completed.

Matching Pairs Game Performance Score The scoring algorithm for the Matching Pairs game was designed to reward accuracy and speed. "Successes" account for 3 points, while "fails" assign 1 point penalty to the player. Additionally, the algorithm implemented a bonus (or a penalty) system for streak matches of "successes" (or "fails"). Finally, the game rewarded players for finishing the game faster. A constant reward was given for completing the game in under 35 seconds, with additional points awarded based on how much faster the completion is relative to this threshold. If the participant did not finish the game in 35 seconds, he did not receive the reward. The details of the scoring algorithm and equations for the Matching Pairs game are shown below:

- the Matching Pairs game performance score (MP_{GP}) is calculated by summing the base score, streak bonuses, and the time bonus in Equation 4.2:

$$MP_{GP} = 3 \times successes - fails + \sum SB_i + TB \quad (4.2)$$

- the streak bonus for the i -th streak (SB_i) is calculated using Equation 4.3:

$$SB_i = \sum [1 + a \times (s - 1)] \quad (4.3)$$

where a is 0.5 for positive streaks ("successes") and 0.75 for negative streaks ("fails"); s represents the number of matches in the streak after the first one;

- the time bonus (TB) is awarded based on the total completion time T , and calculated with Equation 4.4.

$$TB = b \times (35 - T) \quad (4.4)$$

where T represents the finishing time of the Matching Pairs game, b is a factor that depends from T : $b = 0.5$ for $T < 20s$, $b = 0.3$ for $20s < T < 30s$, $b = 0.1$ for $T > 30s$ and $b = 0$ (i.e. no TB) for $T = 35s$.

4.2 EEG Markers and Affective Evaluation of Engagement and Performance in the Snake Game

4.2.1 Introduction

Digital games have increasingly been adopted in experimental research as structured, repeatable tasks that can elicit measurable cognitive and affective responses under controlled conditions. Within this broader landscape, serious games represent one specific category of video games explicitly designed for purposes beyond entertainment, such as education, training, or therapeutic support [206]. While serious games have attracted growing interest in recent years across domains ranging from climate change interventions to psychological support systems, the methodological value of game-based paradigms extends beyond this class of applications. In cognitive science and human factors research, even simple and widely familiar games can provide well-defined interaction rules, goal-directed behavior, and quantifiable performance outcomes, thereby enabling the investigation of perception, attention, and decision-making processes in ecologically plausible yet experimentally tractable settings. A key driver of this trend is the possibility of

integrating game tasks with multimodal sensing to capture both behavioral and physiological responses. For example, eye tracking has been widely employed to characterize visual attention allocation and infer cognitive load during interactive tasks [160]. Such approaches enable the analysis of subtle processing dynamics by linking gaze behavior to task demands, performance, and engagement. As research increasingly aims to understand the moment-to-moment mechanisms underlying information processing during gameplay, EEG has become a widely used technique to obtain a direct measure of neural activity during real-time interaction [206, 400]. EEG supports the investigation of cognitive states such as attention, workload, and mental fatigue, which can be inferred from characteristic changes in spectral power across frequency bands and from patterns of functional connectivity [5, 23]. Gameplay and interactive tasks have been shown to modulate EEG rhythms, with increases in theta and beta activity often linked to elevated cognitive effort and engagement, and decreases in alpha power reflecting reduced relaxation and heightened information processing [166]. Importantly, EEG-based markers are particularly well-suited to capture temporal dynamics, allowing researchers to compare early versus late phases of task execution and to relate neural responses to variations in performance. Alongside objective neural measures, subjective assessments of affective experience are essential to characterize how individuals engage with interactive tasks. Video game play has been associated with changes in positive and negative affect, and may support short-term mood modulation depending on task demands, individual experience, and contextual factors [350]. These effects are frequently discussed in relation to constructs such as perceived achievement and flow [187, 449], which in turn can influence engagement and motivation [290, 468]. Moreover, mood changes during gameplay have been linked to persistence in completing tasks [324], highlighting the relevance of integrating subjective reports with physiological measures when studying interactive contexts.

In this study, the focus was to investigate how playing the digital game of Snake affected participants' EEG activity and affective states. Specifically, participants' EEG activity was compared at the beginning and end of the highest-scoring trial by analyzing spectral power within conventional frequency bands. In parallel, PANAS responses were analysed before and after three gameplay trials to assess potential affective changes associated with task engagement and performance.

4.2.2 Materials and Methods

A total of 22 Italian healthy volunteers (mean age = 26.32 ± 1.94 years, 11 F, 9 M, 2 not specified) were included in the study analyses after performing the experiment described in section 4.1. All EEG data were preprocessed in MATLAB environment using EEGLAB [120] and following the HAPPE framework [164], previously described in subsection 2.3.1 (band-pass filtering 1–48 Hz).

Statistical Analysis To investigate how task engagement and performance influence brain activity, the focus was on the difference in spectral power between the beginning and end of each trial. Specifically, it was formulated the hypothesis that cognitive load and task engagement, as reflected in changes in EEG spectral power, would differ according to the subject’s game performance. To maximize this contrast, the trial with the highest S_{GP} for each participant was selected for EEG-related analysis (see subsection 4.1.3). Participants were divided into two groups: high-performing and low-performing players. This grouping was based on the $median S_{GP} = 26.38$ of the best trial across participants. The distribution of the S_{GP} in the best trial (as shown in Figure 4.4a) confirmed a clear split between individuals who consistently performed poorly ($n_{LP} = 11$) and those who achieved at least one high-scoring trial ($n_{HP} = 11$).

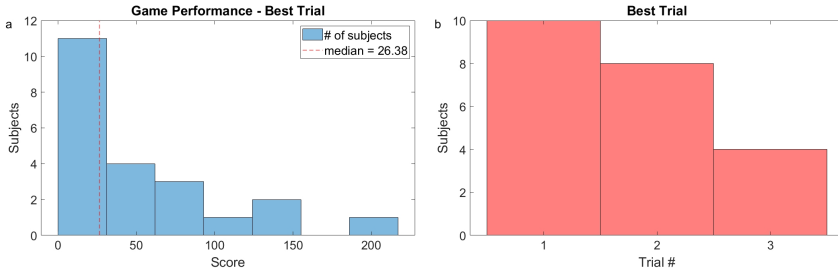


Figure 4.4: (a) Distribution of game performance scores in the best trial for each subject. The red dashed line indicates the median score across all participants (median = 26.38), which was used to divide subjects into high- and low-performing groups. (b) Distribution of the best trial index (Trial 1, 2, or 3) across all participants.

Table 4.1: Mean and standard deviation (std) of game scores for each trial and the best trial, divided between high- and low-performing subjects. P-values refer to the statistical comparison between the two groups using Mann-Whitney U tests (*= $p < .05$, **= $p < .01$, ***= $p < .001$)

	Trial 1		Trial 2		Trial 3		Best Trial	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
High-performing Subjects ($n_{HP} = 11$)	30.97	27.35	67.52	65.13	49.73	52.07	90.9	54.31
Low-performing Subjects ($n_{LP} = 11$)	4.68	5.35	3.43	4.39	2.84	4.12	6.78	5.88
p-value (Mann-Whitney U test, $\alpha = 0.05$)	6.388E-04***		2.925E-04***		0.002**		8.15E-05***	

Although the EEG analysis focused exclusively on the best-performing trial for each participant, game scores were computed for all three trials. This allowed to validate the consistency of the grouping into high-performing and low-performing subjects across all trials. Mann-Whitney U tests were conducted separately on the scores from Trials 1, 2, and 3, and the best trial revealed statistically significant differences between the two groups in every case. As shown in Table 4.1, high-performing subjects consistently achieved higher scores, while low-performing subjects exhibited lower and more stable scores across trials. Notably, high performers displayed considerable variability in performance, suggesting a broader dynamic range in their gameplay outcomes. Among the three trials, Trial 1 emerged as the most successful on average, as further confirmed by the distribution of individual best trials and their associated scores illustrated in Figure 4.4b.

Following EEG preprocessing, the analysis focused on the best-performing trial for each participant. From this trial, two one-second epochs were selected: the initial window (corresponding to the first second of the trial)

and the final window (corresponding to the last second before the end of the game). EEG reaktive power was computed for five canonical frequency bandwidths: delta (1–4 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (13–25 Hz), and gamma (25–45 Hz). For each epoch and frequency band, relative band power was calculated as the ratio between the mean power within that frequency band and the total mean spectral power across the 1–45 Hz range. This yielded normalized measures of spectral activity for both the beginning and end of the trial. Additionally, the change in relative power (Δ) between the final and initial epochs was calculated for each frequency band to quantify the change in neural activity during gameplay. These Δ values were used to assess the topographical patterns of modulation and to identify scalp regions that showed significant differences in power dynamics across participants. Statistical comparisons between these three conditions were then performed using Mann-Whitney U tests (significance level $\alpha = 0.05$), computed separately for each channel and frequency band.

4.2.3 Results

Statistical analysis was performed to compare the relative spectral power ratios between high- and low-performing participants across the five canonical frequency bands (delta, theta, alpha, beta, and gamma), comparing each electrode. Figure 4.5, Figure 4.6 and Figure 4.7 illustrate the scalp distributions for each group and the corresponding statistical significance maps, which were presented in the form of FCSTMs. In the FCSTMs, warm colors denote significantly greater values in the high-performing group (yellow $p < 0.05$, orange $p < 0.01$, red $p < 0.001$), whereas cool colors indicate higher values in the low-performing group (cyan $p < 0.05$, blue $p < 0.01$, dark blue $p < 0.001$). In the initial epoch (Figure 4.5), no significant group-level differences were observed across any frequency band, indicating that the baseline spectral distributions were comparable between high- and low-performing subjects.

In contrast, during the final epoch (Figure 4.6), differences emerged in 4 out of 5 bands. In the delta band, both the left frontal (F3, Fp1 and Fp2) and the right parieto-occipital (P4 and O2) cortices exhibited higher ratios for low-performing participants. This trend also extends into the theta band, where a significantly higher ratio was observed in the left temporal region (T3) for low-performing subjects.

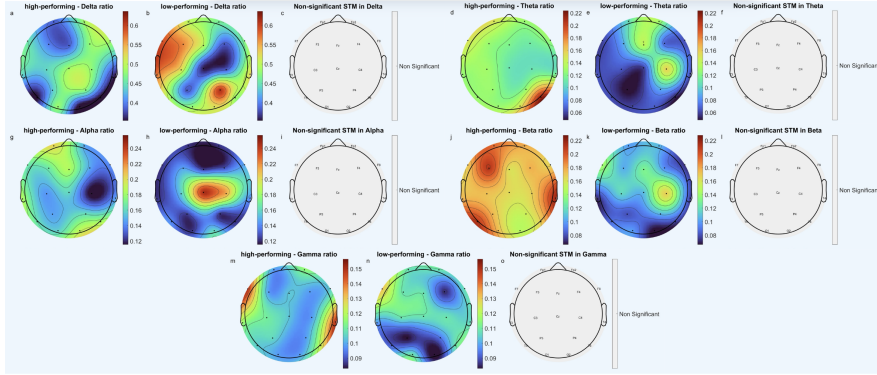


Figure 4.5: Scalp topographies showing the p-values of the Mann-Whitney U tests comparing normalized power from the first epoch between high- and low-performing participants for each frequency band: (a,b,c) delta, (d,e,f) theta, (g,h,i) alpha, (j,k,l) beta, and (m,n,o) gamma.

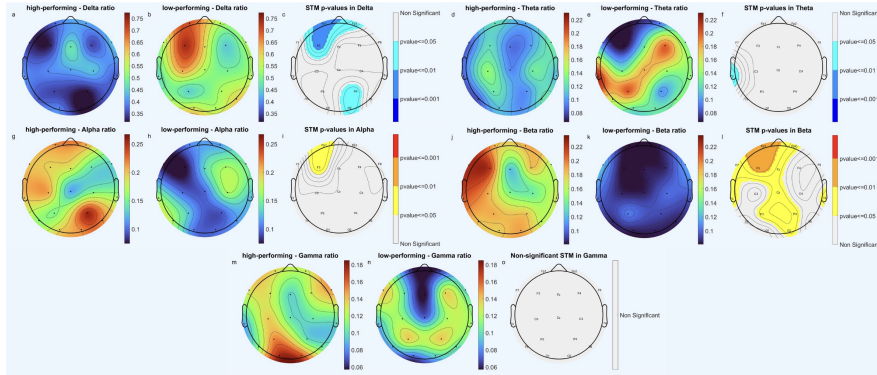


Figure 4.6: Scalp topographies showing the p-values of the Mann-Whitney U tests comparing normalized power from the final epoch between high- and low-performing participants for each frequency band: (a,b,c) delta, (d,e,f) theta, (g,h,i) alpha, (j,k,l) beta, and (m,n,o) gamma.

In contrast, higher frequency bands showed an opposite behavior, with a significant higher alpha ratios in the left frontal area for high-performing participants and a widespread, mainly localized in the left hemisphere (Fp1, Fp2, F7, F3, Fz, Cz, T3, T4, P3, P4, O2), higher beta ratio for high-performing subjects. No significant effects were detected in the gamma band.

When examining the difference between final and initial epochs (Δ ratios, Figure 4.7), additional patterns became evident. Significant group differences were observed in the frontal delta (Fz) and midline theta (Fz, Cz, T3, P3, O1) for low-performing participants. Additionally, alpha ratios in the fronto-central region (Fp2, F7, F3, C3, Cz, P4, O2) showed significantly greater increases for high-performing subjects. No significant group effects were found for beta or gamma activity in the Δ ratio comparison.

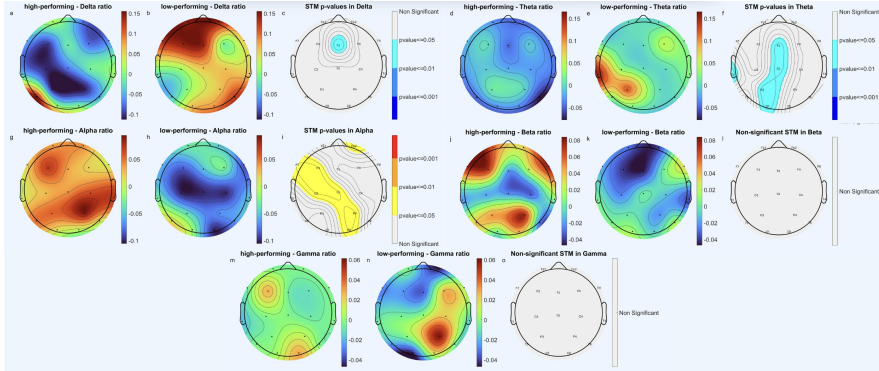


Figure 4.7: Scalp topographies showing the p-values of the Mann-Whitney U tests comparing the difference in normalized power from the final to the first epoch between high- and low-performing participants for each frequency band: (a,b,c) delta, (d,e,f) theta, (g,h,i) alpha, (j,k,l) beta, and (m,n,o) gamma. In the FCSTMs (c,f,i,l,o), warm colors (yellow to red) indicate significantly higher Δ ratios in high-performing subjects; cool colors (cyan to blue) indicate higher Δ ratios in low-performing subjects. Grey indicates non-significant comparisons ($\alpha = 0.05$).

In order to further examine the relationship between EEG modulation and subjective emotional experience during gameplay, additional analyses were conducted, correlating participants' performance scores in their best trial with changes in affective self-reports. Variations in affect were computed as the difference between post- and pre-Snake PANAS scores (Δ PANAS) for

the positive and negative subscales, but also for overall arousal, computed by sum of positive and negative subscales. As shown in Figure 4.8, no significant correlations were found between game performance and either Δ PANAS positive ($\rho = 0.33$, $p = 0.13$) or Δ PANAS negative ($\rho = 0.25$, $p = 0.27$). Conversely, a significant positive correlation emerged between Δ PANAS arousal and performance ($\rho = 0.52$, $p = 0.014$), indicating that participants showing a greater increase in self-reported arousal after the game tended to achieve higher performance scores.

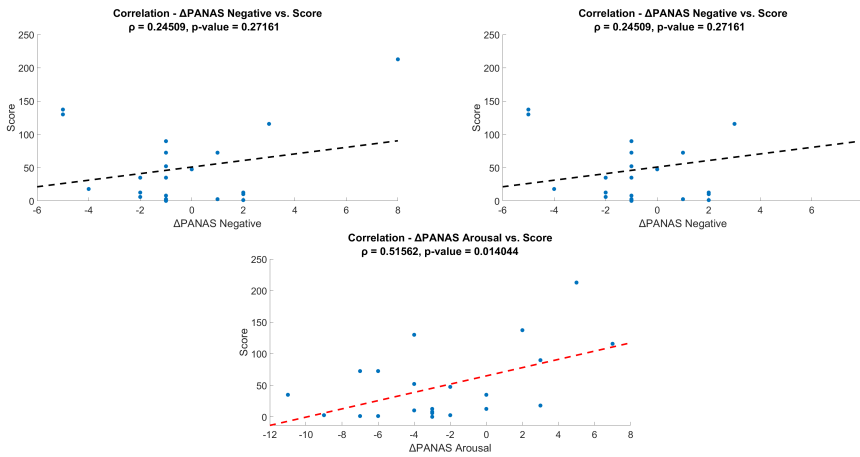


Figure 4.8: Scatterplots show the relationship between participants' performance scores in their best trial and changes in affective self-reports measured by the PANAS questionnaire (post-pre difference). Panels (a), (b), and (c) respectively illustrate correlations for Δ PANAS positive, Δ PANAS negative, and Δ PANAS arousal.

4.2.4 Discussions

The present study aimed to investigate the neural mechanisms underlying performance in a cognitively demanding task presented in a gamified context. By adopting an interactive paradigm based on the Snake game, the study investigated how spectral EEG dynamics evolve in relation to task engagement and performance throughout gameplay. This approach can be extended to the broader field of serious games, where gamified tasks are designed for

educational, training, or rehabilitative purposes. Understanding how neural activity reflects engagement in such contexts may help assess whether a task elicits meaningful cognitive and attentional involvement [93,186].

A key methodological feature of this study was the focus on two distinct temporal windows within each participant's best-performing trial, corresponding to the beginning and end of the game. This design allowed to control for inter-individual differences in task duration while capturing within-task modulation of brain activity. The absence of any significant group differences in the initial epoch (Figure 4.5) suggested that all participants began the task from a comparable baseline of neural activation, consistent with an anticipatory but undifferentiated state before active gameplay.

During the final epoch (Figure 4.5), pronounced differences emerged between high- and low-performing participants. Players with lower performance exhibited increased relative power in delta and theta bands, particularly over left frontal and right occipito-parietal regions (Figure 4.5a-f). Such increases in slow-wave activity may reflect reduced attentional engagement or inhibitory processes associated with decreased task focus [219,220]. Moreover, in tasks requiring sustained visuomotor control, such increases have been interpreted as a neural signature of reduced processing efficiency when task demands exceed the brain's capacity to maintain organized activation patterns. Harmony et al. [191] suggest that increases in delta band activity during mental tasks are associated with functional cortical deafferentation, a process in which the brain suppresses sensory input to support internal processing, potentially leading to less efficient engagement with task-relevant stimuli when cognitive load becomes excessive.

In contrast, high-performing participants showed greater relative power in higher-frequency bands (alpha and beta). Enhanced beta activity, especially over frontal and central areas (Figure 4.5j-l), likely indicates increased cognitive and motor load, reflecting both planning and execution of precise movements required to maintain performance as task complexity increased.

The analysis of Δ ratios (final-initial epochs) further supported these interpretations, revealing distinct patterns of neural adaptation across performance groups. Low-performing participants showed greater increases in frontal delta and midline theta activity, a configuration commonly associated with reduced attentional engagement, heightened cognitive strain, and a shift toward internally oriented processing under increasing task demands [310,381]. In contrast, high-performing participants exhibited more

pronounced alpha-band increases over fronto-central and parieto-occipital regions, consistent with efficient visuospatial integration and adaptive allocation of attentional resources [40,231,398]. As these individuals progressed to more advanced stages of the game, continuous changes in the visuospatial layout required ongoing visual mapping and strategic updating. The observed alpha enhancement, therefore, likely reflects the recruitment of coordinated perceptual and attentional mechanisms that support sustained task performance. These findings suggest that while low-performing participants may experience increasing cognitive overload as task complexity rises, high-performing participants effectively adjust their neural dynamics to maintain engagement and performance efficiency.

The pattern of EEG modulation observed in this study aligns with previous findings linking neural oscillations to engagement during interactive or gamified tasks. In particular, frontal alpha asymmetry has been proposed as a neural marker of emotional and motivational processes, where relatively greater left frontal activity reflects a tendency to approach a stimulus, and greater right frontal activity reflects a tendency to withdraw from it [111]. Moreover, increased beta power has been associated with sustained attention, flow states, and goal-directed motor control in gaming and learning contexts [44,78].

The correlation between Δ PANAS scores and game performance provided further insight into the interplay between affective states and cognitive engagement during gameplay. Although changes in positive and negative Affect did not significantly relate to performance (Figure 4.8a,b), the significant positive association between Δ PANAS arousal and task performance (Figure 4.8c) suggested that participants who reported a stronger increase in physiological and emotional activation after gameplay were also those who performed better. This finding aligns with previous evidence indicating that moderate arousal enhances attentional focus and cognitive performance, particularly in tasks requiring continuous monitoring and rapid motor responses [346]. From a neurophysiological perspective, this pattern converged with the observed increase in beta-band activity among high-performing participants during the final phase of the task. Both results point toward a state of heightened engagement and cognitive-motor readiness, where elevated arousal supports sustained attention, faster reaction planning, and more efficient motor execution. Conversely, participants showing smaller changes in arousal may have experienced lower motivational involvement or

attentional allocation throughout gameplay, resulting in weaker performance outcomes.

These findings support the view that arousal acts as a bridge between subjective experience and neurophysiological activation, modulating task performance in interactive and gamified environments. In fact, they indicate that EEG spectral dynamics can serve as objective indices of engagement, complementing self-report measures [43, 103, 157, 321]. This supports the potential of combining neural and behavioral metrics to monitor user involvement in serious games or cognitive training applications [93, 186].

Despite these promising results, several limitations should be acknowledged. The analyses of this study involved a relatively small sample size (22 participants) and relied on a single best-performing trial per subject, which limits the generalizability of the findings. Future analyses will focus on all three trials per participant and will consider a larger sample of volunteers to enable within-subject and longitudinal studies.

Overall, the present findings indicate that EEG spectral analysis can capture neural signatures of engagement and performance within a gamified cognitive task [37, 73]. These results highlight the potential of EEG-based metrics as indicators of user involvement in serious games, supporting future applications in education, neurorehabilitation, and cognitive training [309, 469]. For instance, such neural indicators could be used to dynamically adapt game difficulty [401] maintaining optimal challenge levels during training sessions. In neuroscience contexts, EEG-based monitoring with a serious game could help with detailed interventions for elderly individuals with MCI [252, 446] by identifying moments of reduced attention and adjusting tasks accordingly.

4.3 Pupil Dilation Dynamics in Matching Pairs Game Emotional Activation

4.3.1 Introduction

Pupil dilation (PD) is controlled by both branches of the ANS: a sympathetic activation directly regulates the dilation neural pathway causing the iris dilator muscle to enlarge the pupil diameter, whereas the inhibition of the PNS, mediated by the locus coeruleus, determines a similar effect by relaxing the iris sphincter muscle, therefore reducing constriction [55, 294].

Pupil size primarily changes in response to light and near fixation. However, several works demonstrated that, in isoluminant conditions, the PD is also sensitive to cognitive activity, which can be elicited by various stimuli such as mental effort tasks or an increased arousal level [294]. Indeed, the relationship between PD and subjective arousal level provoked by picture viewing were found, independently from valence [55, 294]. Moreover, in an emotion-recalling experiment, PD was analysed with nonlinear techniques, i.e., entropy measures, LLE and Detrended Fluctuation Analysis (DFA), to explore its dynamics, highlighting that anger presents a significantly higher scaling factor α_0 concerning happiness, fear and sadness [335]. Beyond audiovisual stimulation, emotion activation can also be induced by playing games [197]. One of the goal of video games, in fact, is to engage the individual and create a bond between them and the virtual world through various mechanics such as quests, stories, puzzles, and time limits [60]. This bond is often expressed through the player's emotional and mood changes [10, 443], and is of great interest for creating immersive environments that may encourage playing games. Indeed, low arousal could result in low interest and involvement [100], therefore precluding serious game purposes. Alongside explicit questionnaires, physiological signals have been widely used to assess game performance and players' emotional status [249]. Preliminary works validated PD as an alternative method for arousal level investigations [245, 246], with respect to the well-known HRV and EDA, also in a serious game for financial decisions [213]. Moreover, a significant difference in the pupil power HF/LF ratio between successful and failed trials has been shown. Pupil size was also used to investigate its relationship with personality traits in a card game, designed to study gambling behaviours [143]. However, these studies applied a set of linear parameters and lacked a similarity analysis between subjective arousal and pupil signal. In this work, a digital version of the Matching Pairs game was used to investigate the relationship between memory skills and pupil diameter and to understand the emotional activation of gaming. Specifically, the aims are three-fold:

1. To investigate whether this simple game can alter the emotional condition of players and modulate their arousal. Such an analysis may underline the use of the Matching Pairs game to train for emotion regulation to help cope with stress and improve quality of life, possibly for older subjects as well [339].
2. To explore possible relationships between arousal levels and pupil linear

and nonlinear metrics. This could highlight reliable alternatives to subjective questionnaires.

3. To understand if and how game performance affects emotion activation and pupil parameters. This represents a first step in proposing the Matching Pairs game combined with eye-tracking technology as an easy, cost-effective technique to study memory skills in young and elderly populations.

4.3.2 Materials and Methods

Twenty-seven Italian healthy volunteers (12 F, 15 M, mean age = 26.3 ± 3 years) were included in the study analyses after performing the experiment described in section 4.1. All participants gave written informed consent. Pupillary analyses were performed in MATLAB. Pupillary signals were pre-processed as previously described in section 2.6 (Figure 4.9). PANAS scores were normalised with a z-score-like procedure by subtracting the median value and dividing by the MAD. The mean MP_{GP} across the three trials of the Matching Pairs game was calculated following the score algorithm reported in subsection 4.1.4.

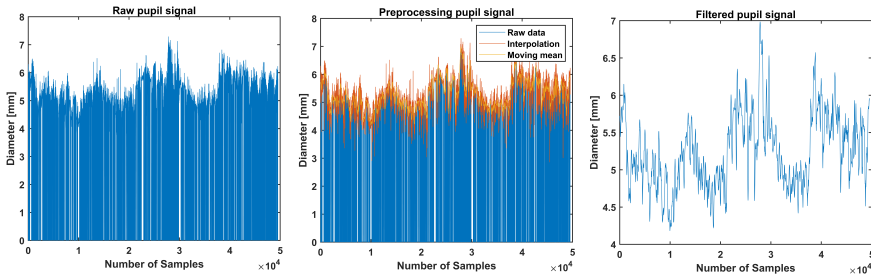


Figure 4.9: Pupil diameter preprocessing pipeline. Left panel: raw pupil signal. Middle panel: artifacts removal and filtering. Right panel: cleaned pupil signal.

For each participant, six statistical parameters were extracted from the PD, as previously described in subsection 2.6.1. Also, their GP scores were calculated as reported in subsection 3.1.4.

Statistical and correlation analysis The normality hypothesis was rejected with a Shapiro-Wilk test with α -level of significance set to 0.05. Therefore, the first hypothesis explored whether playing a matching pair card game provokes an alteration in the emotional status of participants with a Wilcoxon signed test. The second hypothesis investigated if the difference in PANAS scores (positive, negative and arousal) before and after playing showed possible relationships with physiological parameters. Finally, it also considered how game performance affected emotion activation and PD metrics: subjects were divided into high and low performance based on the median score value.

4.3.3 Results

Figure 4.10 shows that playing the three trials of Matching Pairs game significantly increased positive emotions (p -value = 0.04) and simultaneously determined a decrease of negative emotions (p -value = 0.002). However, the overall arousal level, computed as the sum of positive and negative emotions was not significant (p = 0.06).

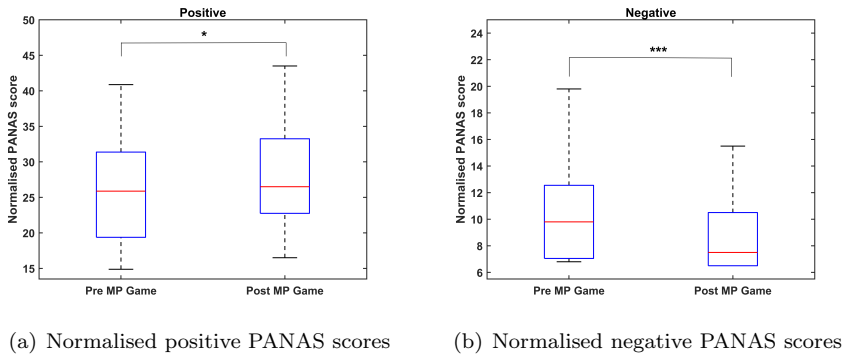


Figure 4.10: Statistical analysis results on psychometric scores.

Spearman correlation analysis was performed considering the difference between post- and pre-game PANAS scores and PD parameters. As Table 4.2 displays, arousal and positive difference scores are weakly, but significantly, correlated to LLE, whereas negative difference scores are associated with the STD of pupil diameter.

Table 4.2: Correlation analysis between the difference of PANAS score and PD parameters.

Parameters	ρ
Arousal $\longleftrightarrow$ LLE	0.41
Positive $\longleftrightarrow$ LLE	0.40
Negative $\longleftrightarrow$ STD	0.41

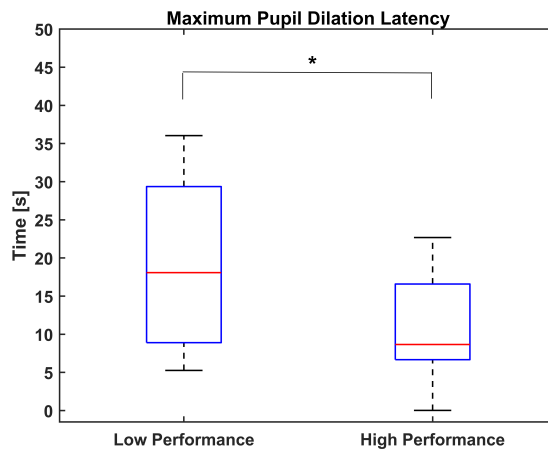


Figure 4.11: Maximum pupil diameter between high and low-performance players.

As for the third hypothesis, game performance did not affect any of the PANAS scores. However, a t-test highlighted that the latency of the maximum PD presents a significant difference between players who achieved high performance with respect to low-performance subjects. Figure 4.11 shows the boxplot for this feature. Median (iqr) of game performance is 28.1 (11).

4.3.4 Discussions

Game dynamics such as winning and losing can effectively boost emotions, e.g., positive emotions when money is won in fictitious gambling games [263]. However, little research focuses on this aspect of serious games. Besides entertainment, these games are designed to analyse and stimulate specific human behaviours (e.g., memory skills), but if arousal is not considered

when developing such applications, this could lead to poor interest and lack of motivation in players, therefore hindering the usability and usefulness of serious games themselves. This study demonstrates that even a simple Matching Pairs game can elicit an emotional activation in healthy and young players, which is likely caused by the fact that most of them completed the three trials successfully. Indeed, Figure 4.10 show a concurrent increase in positive emotions and a decrease in negative ones. Nonetheless, the overall degree of arousal was not significant, which may suggest that players are not relevantly involved in the game. Therefore, in the future, this aspect should be considered in the game design, e.g., by increasing the number of cards between single trials. To obtain objective parameters of players' arousal, pupillometric features were extracted and analysed. Table 4.2 shows that higher positive emotions are related to a complex activation of the autonomic nervous system reflected in larger LLE, which may mean that higher positive emotions evoke more chaotic pupil muscle activity. Similarly, lower negative emotions determine higher STD values, which suggests that pupil dilation patterns present higher instability. However, this effect may be marginal as Table 4.2 shows that the overall level of arousal significantly depends on nonlinear dynamics. Game performance can affect the degree of emotional activation [10, 263]. Results showed no significant difference in PANAS scores between high and low performance. This may indicate that arousal, positive and negative emotions do not differ for this Matching Pairs game. This could be caused by the limited number of subjects for each group, and in future studies, the sample size must be increased to validate such an outcome. However, a significant difference was found in pupil behaviour: indeed Figure 4.11 shows that the latency of low performance players is higher with respect to high-performance ones. This parameter is thought to reflect the allocation time of cognitive resources. It seems that more time is required to process and identify a game strategy for low-performance participants. These results suggest that the Matching Pairs game may be effectively used to analyse memory capabilities. Therefore, a gamified approach could provide a range of exercises in elderly care and rehabilitation for both the psychological well-being of older adults and their cognitive skills. Further research should explore this topic in the future. Summing up, a serious game based on matching pairs of card games determines an alteration of the emotional status of participants, which is also supported by physiological assessment. This framework could be useful to objectively

validate the degree of engagement of participants while playing a serious game.

4.4 Multimodal Analysis of Emotions in Gaming: Understanding Cultural Influences

4.4.1 Introduction

This study introduces an innovative multimodal approach that integrates AI-based, FER, and ANS response to investigate the profound effects of video games on human emotions. This work seeks to answer a fundamental question: *"How do video games influence individuals' emotional states across different cultural contexts?"* Over the past decade, video games have become a prevalent form of entertainment, widely consumed by billions of people worldwide across diverse demographics. Driven by rapid technological advancements, the video game industry has experienced significant growth, offering a variety of games that appeal to a broad audience [290,403]. This global gaming community includes individuals of all ages and backgrounds, highlighting the substantial cultural and economic impact of video games [403]. Although emotional reactions in video games have been examined using and adapting various techniques, such as ANS measurements [318,432,456] and FER [49,50,222,458], most studies have been conducted within a single cultural context and rarely account for the sociocultural background of players. This limitation is consistent with findings from a recent systematic review on the cultural impact of video games, which highlights strong geographical biases, a predominance of qualitative approaches, and a limited consideration of how cultural background shapes players' interpretation and experience of game content [74]. Consequently, the role of culture in modulating emotional responses during gameplay remains largely unexplored, representing a significant gap in the current literature.

One of the most widely applied approaches to investigate emotions has been through FEs [82,124], and in recent decades, several models have been proposed [76,221]. However, FEs can be voluntarily modulated and therefore may not always provide reliable indications of a person's emotional state. Peripheral physiological signals, such as the ECG and, in particular, its derivative metric, HRV, offer complementary insights into ANS modulation of cardiovascular dynamics. The ANS constitutes a central bidirectional interface

between brain, bodily states, and emotional processes, and emotional stimulation induces systematic adjustments in autonomic output via coordinated limbic and cortical pathways [178]. Although recent works have shown that ANS responses do not map reliably or specifically onto discrete emotion categories [201,396,440], the heart rate dynamics can reflect broad dimensions of autonomic arousal and regulation. By integrating behavioural signals with HRV derived from ECG, this research aims to capture these dimensional autonomic changes during gameplay, rather than inferring discrete emotional categories. This combined behavioural and physiological approach advances the comprehension of the emotional impact of gaming. It provides a foundation for designing more immersive experiences and therapeutic applications, as well as for encouraging healthier gaming practices [223,442].

In this methodological framework, advanced AI-driven techniques along with biosystem modelling approaches are combined. Specifically, a Machine Learning (ML)-based FER model, enhanced with Markov Chain (MC) modeling to interpret transitions between emotional states is implemented. Additionally, HRV metrics are extracted from ECG recordings to explore the dynamics of ANS in response to gaming stimuli [413]. Furthermore, Generalized Linear Mixed-Models (GLMMs) were fitted to assess the dominance of specific emotions and to determine whether cardiovascular dynamics could be altered by players' performance. A key methodological contribution of this study lies in its explicit cross-cultural structure. Rather than restricting the analysis to a single cultural setting, the present research investigates variations in emotional expressions and ANS responses across distinct cultural groups. This analysis of emotional reactions in gaming contexts could enable the design of more engaging and emotionally resonant games, offering crucial insights for developers and researchers aiming to optimize the user experience. Moreover, these insights will support the development of strategies to mitigate the emotional impact of gaming, ensuring that it remains a positive and healthy activity for the diverse range of players.

FER, AI and Human Emotions In recent decades, AI has evolved from niche applications to an integral part of daily life, transforming human-machine interactions [193]. AI broadly refers to using computational power to mimic human cognitive abilities [86], enabling automation, problem-solving, and augmentation across various tasks [83,267,325]. Its widespread adoption enhances efficiency across multiple domains, from autonomous vehicles nav-

igating complex environments [420,428] to creative content generation [183]. In healthcare, AI supports medical diagnosis and treatment planning [463], while in human resources, it streamlines recruitment processes [418]. One of the crucial applications of AI is Computer Vision (CV), which enables machines to interpret visual data like humans [412]. CV techniques, such as image acquisition and analysis, support applications in risk management and biological research [455]. Compact models now allow CV to function on mobile devices. FER has gained prominence in this domain, aiming to decode human emotions through facial analysis [8,302]. Currently, complex convolutional neural networks (CNNs) dominate FER research, using the Facial Action Coding System (FACS) developed by Ekman to classify emotions based on facial muscle movements [128,138]. FACS has proven instrumental in decoding seven core emotions (*angry, disgust, fear, happy, neutral, sad, and surprise*), making it a gold standard for FER applications [253]. Numerous ML techniques, including support vector machines [167], random forests [447], and deep belief networks [358], rely on this system to improve emotion-detection accuracy.

FEs, which form the basis of FER, are widely regarded in the literature as communicators of emotional states, functioning as expressive and adaptive signals that bridge internal experiences with external social contexts [208]. Specifically, from the early stages of human development, expressions such as the social smile foster connections and secure caregiver bonds. In contrast, distress signals ensure survival by eliciting protective responses from others [52,136]. Scholars from Charles Darwin to Paul Ekman have emphasized the evolutionary importance of these expressions in enhancing social cohesion and species fitness [109,136]. Furthermore, Ekman's extensive cross-cultural studies have shown that while the basic patterns of FE are universally recognized, the intensity of these expressions is modulated by cultural norms [134,296]. Many findings highlight the importance of cultural context in FER models, emphasizing the need to integrate diverse datasets to improve the technology's generalization and robustness [134].

Although FEs have historically been treated as reliable indicators of internal emotional states, recent empirical research demonstrates that the relationship between "facial movements" and experienced emotions can neither be fixed nor exclusive. Facial movements refer to the patterned activations of individual or combined facial muscles, and these coordinated muscular actions collectively form what are recognized as FEs [35]. Large-scale reviews

show that the same facial movement patterns, such as smiles, can emerge across a wide range of emotional and non-emotional contexts [35]. Moreover, Duran and Fernández-Dols showed that in their meta-analysis, the predicted configurations for so-called basic emotions co-occur with their corresponding emotional states far less consistently than previously assumed, suggesting that observable facial movements cannot be interpreted as one-to-one emotional readouts [133]. In addition, an experimental study with trained actors also demonstrates substantial variability in facial movements produced for the same emotion labels, supporting the idea that context strongly shapes how emotions are expressed and perceived [256]. Lastly, comparative studies using both human raters and automated classifiers show that neither can reliably infer felt emotions from facial movements alone [426]. Nevertheless, these convergent findings remain subject to debate in the literature, as FEs can sometimes align with emotional experience [138] and at other times diverge from it [35]. This variability reflects the influence of multiple concurrent information, including physiological responses, contextual cues, and cognitive appraisals, all of which shape how emotions are expressed and interpreted.

Human emotions, often described as psycho-physiological phenomena, have been analyzed through various scientific methods. These include measuring ANS responses, such as HRV [16] and EDA [70], alongside CNS responses observed through EEG [104]. Additionally, emotions manifest through nonverbal signals like posture, speech, and behavioural changes [105]. Considering their complexity, a single modality cannot fully capture the interplay of physiological, cognitive, and contextual factors. Studies indicate a strong correlation between HRV patterns and specific emotional experiences. This suggests that a combined multidomain approach utilizing FER and ANS analysis could provide a more accurate understanding of human emotions [225,356]. This interdisciplinary synergy between behavioural and physiological analysis enhances the precision of emotion-recognition technologies, paving the way for more nuanced AI systems capable of interpreting human emotions with greater efficiency and applicability across diverse real-world scenarios.

Video Games, Emotion Studies in Video Games, Arousal and Valence The growth of affordable internet access and the integration of technology into daily life have significantly expanded the reach of video games.

Recent surveys estimate that there are currently 3.32 billion active video gamers worldwide, highlighting the massive audience that engages with this activity [204]. In addition, video games are widely popular among people of all ages, from children to older adults. The average gamer is around 35 years old, and games appeal to various interests, reaching a wide age range [403]. Despite this considerable reach, there are differing opinions and research on the impact of video games on individuals. This diversity of perspectives underlines that video games can have positive and negative effects [150, 172, 352].

Although video games can be analyzed across a broad spectrum, one of the most affected aspects is players' emotional activation. The diverse mechanics and high levels of immersion in video games uniquely influence players' emotional experiences. Players often experience a range of emotions, from *sad* and *happy* to *disgust* and *fear*, within a single gaming session [13]. These emotional responses are linked to the interactive nature of games, which require active participation in narratives and decision-making processes and to performance-related outcomes, where success or failure in the game can significantly impact a player's emotional state.

Various studies have examined the relationship between video games and emotions. For example, Przybylski et al. [353] found that video games that satisfy basic psychological needs, such as competence and autonomy, can increase players' positive emotions and overall well-being. Conversely, a study by Lemmens et al. [264] found that time spent playing violent games specifically increased physical aggression. They also found that excessive gaming could elicit more negative emotions. Furthermore, higher levels of pathological gaming (e.g., gaming addiction), regardless of violent content, predicted increased physical aggression in boys. Nevertheless, these studies, and many others in the literature, focus primarily on psychological aspects, relying on self-report measures rather than integrating physiological or behavioral data to understand the emotional impact of video games on individuals.

The interplay among psychological and physiological variables and contextual elements, such as environmental factors and specific stimuli, is crucial in shaping emotional arousal and valence. In the context of video games, these dimensions serve as key descriptors of players' emotional states, based on the circumplex model of emotion [367]. Arousal reflects the degree of emotional intensity or activation, spanning a spectrum from low to high [89]. Studies indicate that video games of different genres variably in-

fluence arousal levels, underscoring the importance of both the game's genre and its mechanics, including aspects like scoring systems, time constraints, and platform type [216, 239, 303]. Valence, on the other hand, characterizes the positive or negative quality of an emotional experience, influencing not only player performance but also their overall engagement with the game [33, 42, 162, 289].

These emotional dimensions are intricately linked to physiological responses during the gameplay. For instance, Hazlett's study utilizing electromyography (EMG) identified negative emotional reactions during high-intensity gameplay, even in scenarios where cognitive load might confound results [195]. Yeo and colleagues explored competitive gaming environments, specifically analyzing "League of Legends", and discovered that physiological markers such as HRV, pulse transit time, and skin temperature indicated increased sympathetic activity, with a concurrent decrease in parasympathetic function during gameplay [460]. These findings suggest that different genres of video games may elicit distinct physiological effects.

As immersive and dynamic experiences, video games offer a strong medium for eliciting complex emotional responses and have been widely used in the literature for this purpose [179, 405, 471]. Defined as interactive digital experiences that engage players through compelling narratives and challenges, video games utilize audiovisual elements to create richly immersive environments, either story-driven or task-oriented [142, 257]. These environments are designed to provoke a spectrum of emotions, from joy and excitement to frustration and anxiety, all closely tied to in-game events and player performance [42, 149, 262, 384].

HRV as Index of ANS and Psychophysiological Regulation HRV reflects the fluctuation in time intervals between consecutive heartbeats, typically measured as RR intervals in the ECG, and is a key physiological marker of ANS function. It captures the dynamic interplay between sympathetic and parasympathetic modulation of cardiac activity, with higher HRV generally associated with better cardiovascular health and adaptive autonomic regulation [17]. Conversely, reduced HRV is linked to pathological conditions such as cardiovascular disease, stress, and autonomic dysfunction [334]. The interpretability of HRV components has been refined through recent psychophysiological research. High-frequency (HF) HRV is widely accepted as a selective marker of cardiac parasympathetic activity because of its tight

coupling with respiratory rhythms, while low-frequency (LF) HRV reflects a mixture of sympathetic and parasympathetic inputs rather than pure sympathetic tone [355]. In parallel, the association between HRV and emotional or cognitive states has been extensively documented. Higher HRV is typically indicative of stronger parasympathetic influence, whereas emotionally arousing or cognitively demanding conditions tend to reduce HRV due to increased sympathetic activation. HRV has thus been validated as a reliable marker of psychophysiological stress and emotional engagement [51, 395]. For instance, challenging cognitive tasks or emotionally stressful events can induce a shift in HRV power toward sympathetic dominance, reflecting heightened arousal [51]. Beyond time- and frequency-domain indices, nonlinear HRV features provide enhanced sensitivity for characterizing psychophysiological states. Methods such as Recurrence Quantification Analysis (RQA) [438] capture dynamical properties of cardiac regulation that are not accessible through linear metrics alone. Evidence indicates that RQA-derived measures can discriminate levels of cognitive engagement and physical stress over short time windows and may perform comparably or better than traditional HRV measures when assessing interpersonal synchrony and autonomic adaptation [438].

This study aims to explore FE responses of players engaged in two distinct video games, "Matching Pairs" and "Snake", employing a CNN. The focus is on analyzing FE and physiological signals, such as HRV, to unravel the multimodal dynamics of emotional reactions, emphasizing how different cognitive demands and game mechanics, such as performance, influence these responses. Literature has mainly focused on single cultural contexts; in contrast, the novelty of this study is based on its cross-cultural scope, comparing participants from Korea, Italy, and Japan to reveal how cultural backgrounds shape emotional and physiological reactions during casual video games.

4.4.2 Related Studies and Study Structure

Emotions are phenomena shaped by different types of stimuli, continuously fluctuating in response to situational factors [332]. Specifically, in gaming contexts, these fluctuations can be influenced by a wide range of variables, including task demands, interaction dynamics, and individual differences [53, 432, 458]. In this regard, the present study adopts a cultural perspective to examine these processes, moving from general indicators to more specific

ones to better capture the complexity of emotional responses.

More specifically, the Step Ia provides a broad, static overview by examining overall distributions of FEs across cultures. This step recognizes general patterns of FE, establishing how different cultures outwardly experience FE during gameplay. Building on this, Step Ib strengthens the dynamic analysis by focusing on and evaluating core FE patterns across different contexts. This strategy helps for a more comprehensive understanding of cross-cultural differences before introducing temporal dynamics. Consequently, Steps I and Ib together form an integrated approach that characterises the static and dynamic structure of FE. Lastly, Step II focuses on the underlying mechanisms by analyzing physiological signals, particularly HRV, to reveal how physiological processes accompany and regulate both expressions and their temporal dynamics. Through this progression from static analysis of FEs to dynamic changes, and finally to physiological responses, the outcomes establish a coherent path from general patterns toward more specific mechanisms.

Step Ia: Static Distribution of FEs Across Cultures

Various studies in the literature highlight the significant influence of culture on emotional experience and expression [134, 139, 296]. For instance, the Italian population, shaped by historical and cultural developments, tends to prioritize pleasure, embodying a more hedonic lifestyle compared to other cultures [159]. This lifestyle strongly influences their motivations, including those related to video games. In a study by Gursesli et al., "entertainment" emerged as one of 12 distinct motivational clusters and was particularly favoured by Italian gamers [181]. This finding highlights how cultural differences shape daily preferences, including those related to casual activities, leading to the first research hypothesis:

Hypothesis 1.1 (H1.1). Italian cultural group is expected to exhibit a higher probability of happy FE and a lower level of negative FE compared to Japanese and Korean cultural groups while playing Snake and Matching Pairs games.

Asian cultures, particularly in video games, emphasize competitiveness, often leading to a higher display of negative emotions [228, 230]. Negative emotions can generally be divided into two major categories: action-oriented and inhibition-oriented. Action-oriented emotions, such as *angry* and *dis-*

gust, typically drive people to take action. Conversely, inhibition-oriented emotions, such as *fear* and *sad*, lead to passive or avoidant behaviour, often resulting in disempowerment. In the case of Japan, for instance, the expression of certain negative emotions, such as *fear*, is more restrained due to the country's collectivistic nature and the implicit rules governing emotional displays [137, 370].

Whereas individualistic cultures, such as those in the West, prioritize authenticity in all its forms, collectivistic cultures emphasize adapting one's behaviour to the interlocutor to avoid social impropriety. This tendency to "mask" emotions is particularly pronounced in Japan's highly status-conscious society [106], where individuals suppress expressions of *fear*, especially in the presence of authority figures such as an experimenter [297]. Furthermore, qualities such as fearlessness, integrity, and bravery have long been revered in Japanese philosophy and culture, as seen in traditions such as Bushido, Shintoism, Confucianism, and Buddhism [114]. Although these ideologies may not directly dictate the suppression of *fear* [113], they have shaped social norms and implicit rules of emotional display that likely influence such behaviour and may serve as moderating factors. Apart from the *fear*, Japanese culture is also known for its competitive mindset, which is also related to negative emotions [66, 207]. Considering this literature, the following hypothesis can be formulated:

Hypothesis 1.2 (H1.2). Japanese cultural group is expected to be less likely to show fear FE compared to Italian and Korean cultural groups while playing Snake and Matching Pairs games.

Studies show that Koreans frequently express negative emotions and show this expression both verbally and non-verbally in reaction to a variety of social and personal triggers. Studies by M. Kim [226, 227] and Y. Kim [229] have revealed that emotions such as *sad*, *angry*, *disgust*, and shame are frequently experienced, especially in situations involving personal failure [391]. This characteristic may be linked to the competitive nature of Korean society, where high expectations and pressure to succeed are prevalent [410]. In this sense, academic, career, or social competition can lead to frustration and increased sensitivity to failure or perceived incompetence. Moreover, several studies show that this competitive cultural structure is also effective on video game players [81]. In addition, literature shows that competitive

behaviours are related to negative emotions [161,177]. Taking these studies into account, it can be stated:

Hypothesis 1.3 (H1.3). Korean cultural group is expected to be more likely to show negative FE compared to Italian and Korean cultural groups while playing Snake and Matching Pairs games.

Overall, in this step, the focus on *happy* and *fear* in *H1.1* and *H1.2* are grounded in culture-specific findings. Italian cultural psychology research [159] highlights a strong hedonic orientation, making *happy* a particularly relevant emotion for examining expressive tendencies among the Italian cultural group. In contrast, Japanese cultural groups consistently report that *fear* is the emotion most likely to be suppressed due to collectivistic norms and sensitivity to social hierarchy. For Korean cultural group, previous research does not emphasize one specific emotion. Instead, the literature describes a broader pattern of competitiveness-related negativity that spans multiple negative FEs. For this reason, *H1.3* was formulated at the level of overall negative valence rather than at the level of a single discrete emotion.

Step Ib: Dynamic Transitions of FEs Across Cultures

People's emotional state dynamics are essential in the context of video gaming. Video games, especially when offering high cognitive content, elicit rapid changes in the subject's emotional state, which, on a social and nonverbal level, are mainly expressed through changes in facial features [109,136]. This dynamic structure, while emerging from distinct facial patterns associated with different emotions, should also be considered in light of one of the most critical metrics influencing affective responses, i.e., cognitive load. Although emotional responses span a wide spectrum, they are highly sensitive to variations in cognitive demands, which can rapidly modulate how individuals experience and express affect. The literature has shown that affective states are not merely a reaction to external stimuli and cognitive activities. For instance, studies investigating performance in complex cognitive tasks such as goal attainment [198], school exams [108], or competitive sport [451] activities have shown that success or failure in task execution directly shapes participants' emotional states. High cognitive load often leads to negative emotions such as sadness, whereas successful performance under demanding conditions is typically associated with positive emotions such as happiness.

These results highlight that cognitive processes and emotional states are

crucial for understanding how emotions evolve and change during dynamic events such as video games. Specifically, the link between emotions and cognitive load in video game contexts has been investigated in several studies [79, 385]. According to Yeh et al. [459], an analysis considering the complex time-varying dynamics of emotional states was also implemented. Moreover, the main research question was how different types of video games affect players' FE, as the Snake game is mainly based on reactivity and speed. In contrast, the Matching Pairs game involves more mnemonic and attentive processes.

Accordingly, initially a self-reported questionnaire was employed to assess participants' emotional states. To this end, a preliminary analysis was conducted on participants' game performance and their scores on the PANAS questionnaire. However, self-report questionnaires are subject to self-report biases, such as participants' tendency to provide socially desirable answers (e.g., honesty bias) and their limited ability to accurately assess their own emotional states (e.g., introspective ability) [12, 122]. Furthermore, these tools are limited to capturing emotions at two fixed points (before and after the experience) and are not well-suited to analyzing the dynamic, instantaneous changes in emotional states during gameplay. To overcome these limitations and gain a more continuous understanding of emotional dynamics during gameplay, a MC-inspired approach [404] was used to model transitions between different emotional states over time.

This approach allows for the investigation of emotional transitions in subjects looking for time-variant emotional patterns that can identify differences in the different populations, both in the cultural context and game performance. Step Ib aims to investigate how FE dynamics evolve in response to game-related stimuli and how these patterns vary across cultural, cognitive, and contextual factors. Specifically, the analysis focuses on identifying whether participants from different cultural backgrounds exhibit distinct temporal patterns in their FEs, exploring also how individual differences in task performance relate to variations in these dynamics, and examining the extent to which the type of game shapes the temporal structure of emotional transitions.

Step II: Multimodal Integration of FE and HRV Data to Model Gameplay Performance

This step investigated ANS changes during gameplay and their relationship with FEs and cultural background. The focus was on acquiring ECG signals, which were used only to extract HRV, the time-interval variation between consecutive heartbeats. It is widely recognized as a way to assess ANS behaviour in terms of sympathetic and vagal branch functions, both in normal and pathological conditions [436]. The HRV has also found applications in video game studies, helping researchers assess players' stress levels, emotional responses, and engagement [205] while providing valuable data for adaptive game design [454] and therapeutic interventions [368, 369]. Recently, these findings have led researchers to design biofeedback-based games that use HRV features to manage stress and maintain optimal arousal levels, thereby improving gameplay experiences and mental well-being [77, 80, 144]. The integration of HRV data allows for Dynamic Difficulty Adjustment [274, 326], enabling games to adapt in real-time to players' physiological states, ensuring a balanced challenge that keeps them engaged without being overwhelm. However, HRV analysis in different cultures, in the video games context, is limited to bio-feedback applications and is not considered for exploring the underlying cognitive processes during games. Finally, Step II aims to examine how ANS activity, as captured by HRV, interacts with FE patterns to shape players' behavioural responses during gameplay across cultures. The analysis focuses on determining whether multimodal physiological and emotional signals offer complementary insights into task performance, exploring how HRV-based indices of autonomic regulation relate to variations in emotional expression across the session, and assessing whether these relationships differ by game type and players' cultural background.

4.4.3 Materials and Methods

Materials

Participants and Experimental Procedure A total of 129 healthy volunteers from three different cultures participated in the experimental sessions (see section 4.1). 109 of them, comprising 30 of Italian culture (mean age = 26.1 years, 13 F, 15 M, 2 non-specified), 40 of Korean culture (mean age = 24.375 years, 9 F, 30 M, 1 non-specified), and 39 of Japanese culture (mean age = 23.38 years, 3 F, 35 M, 1 agender) were included in the study analyses.

The overall mean age of the participants included in the study analyses was 24.5 ± 3.5 years.

FE data was obtained by means of WAFER and aligned with Ekman's theoretical constructs of seven primary FEs (*angry, disgust, fear, happy, neutral, sad, and surprise*) delivering results as cumulative percentages that collectively sum up to 100% [136, 138], as these values are continuous for each emotion category. WAFER outcomes are provided at a $f_s = 1Hz$ during the experimental sessions, enabling continuous emotion classification and analysis of dynamic emotional shifts during gameplay.

According to their performance, players were then categorized as either high-scoring or low-scoring for each game (see subsection 4.1.3 and subsection 4.1.4). Specifically, this classification was based on the median game performance (GP) scores of the population, allowing for the distinction between participants with higher and lower task proficiency and for investigating how skill level modulates emotional and cognitive responses during gameplay. The scoring analysis identified 54 high-scoring and 55 low-scoring individuals for the Snake game ($median = 12.69$, $mad = 18.14$, $max = 141.11$, $min = 0$), and similarly, 54 high-scoring and 55 low-scoring individuals for the Matching Pairs game ($median = 28.6$, $mad = 7.39$, $max = 41.83$, $min = -17.98$).

Methods

This section outlines the methodological framework of the study, which integrates a multimodal set of tools to examine emotional and physiological responses during gameplay. In this study, specifically in Step Ia and in Step II, a GLMM approach was implemented, as it represented the most appropriate framework for the data structure. Unlike repeated-measures ANOVA, which requires normally distributed residuals and equally spaced observations, GLMMs flexibly accommodate repeated measures and non-normal outcomes, such as skewed facial-expression activations and game performance scores. Similarly, although Generalized Estimating Equations (GEEs) handle correlated data, they estimate only population-level effects and do not allow subject-specific random effects, which are essential in this design given the large variability in emotional and physiological responses across participants. Specifically, in Step Ia, the primary goal was to compare FE activations across cultures and game types, whereas Step II focuses on predicting game performance from FE and HRV features.

Moreover, in Step Ib the GLMM analysis of Step Ia were complemented with a MC-inspired approach to capture the within-session temporal dynamics of FE states. Although GLMMs are well-suited for estimating trial-level effects and participant-level variability, they do not explicitly model how emotional states unfold over time or how the probability of observing a given state depends on the immediately preceding one. MC modelling, by contrast, provide a principled framework for quantifying state-to-state transition probabilities, allowing to examine patterns of FE expression activation during gameplay. Although the current literature does not supply prior studies applying first-order MCs directly to FER time-series, the affective-computing literature widely employs Hidden Markov Models (HMMs) to model temporal dependencies in emotion recognition tasks, including FEs [47, 244, 382], speech [286, 329, 386], and human affective states [273]. Similarly, transition matrix approaches have been used in affective gaming and human-computer interaction to analyze how players move between behavioural or psychophysiological states over time [320], supporting their use in characterizing temporal structure in emotionally driven interactions. Thus, Step Ib employs a MC-inspired approach as an interpretable and data-efficient method to quantify transitions between detected FE states during gameplay. Finally, in Step II, the analytical framework is extended by integrating HRV features into the GLMMs to jointly evaluate how FE and ANS-related physiological dynamics contribute to task performance.

GLMM for Step Ia: behavioral analysis Given the repeated measurements of FE activation (one evaluation per second for each emotion), a GLMM was used to examine differences between the three samples across the two game modes (i.e., Snake and Matching Pairs). Specifically, in this study, the emotion variable was treated as a continuous dependent variable. Effect magnitudes are conveyed through standardized regression coefficients (β) and model F-statistics. Pseudo- R^2 indices were not reported for these models, as their interpretation is less straightforward in the context of high-frequency, multi-response GLMMs. GLMM was implemented using SPSS v.1.2.4.0. In the model, game type was treated as a condition, while emotion was the dependent variable. Cultural demographic information was included as a fixed factor, with Korea as the reference category. Model comparisons were conducted using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to evaluate model fit and prevent overfitting.

GLMM for Step II: multimodal domains integration In this step, GLMMs integrating FE and HRV-related features have been implemented to analyze their impact on task performance in the Snake and Matching Pairs games. Four separate GLMMs were developed for each game:

- A model including only FE-related features (10);
- A model encompassing only a 'canonical' set of HRV features, comprising time-frequency domain and entropy-based HRV features (22);
- A model including only a specific set of non-linear HRV features – namely 'complex' – comprising fractality, self-similarity, and recurrence quantification analysis (RQA) -derived measures (10);
- A model incorporating all previous features combined (42), reported in an extended form in section A.2, Table A.1.

All GLMMs implemented for this step (SPSS v.1.2.4.0) used a gamma distribution with a log link function for the dependent variables, given the skewed distribution of game performance scores in both the Snake and Matching Pairs games. Participants' cultural background was included as a random effect in all GLMMs. Preliminary analyses showed no significant differences in HRV features across cultural groups, consistent with the expectation that cardiovascular dynamics in healthy individuals show minimal cross-cultural variability. However, since culture had emerged as a potential confounding factor in the analysis of FEs, modelling it as a random effect allowed to account for residual intergroup variability without assuming systematic differences attributable to cultural background. Model comparisons were conducted using the AIC and BIC to evaluate model fitting and avoid overfitting. Additionally, the Conditional R^2 (R^2_{cond}) was used to assess the model goodness-of-fit.

Positive and Negative Affect Schedule PANAS was used to assess participants' emotional states. As previously described in section 2.9, three different version of PANAS were administered to participants, based on their cultural background. Being that the Korean version of PANAS presented 9 positive items and 11 negative items, different from Italian and Japanese versions (10 positive and 10 negative items), for PANAS-related analyses mean

scores were used instead of summed scores to account for these differences in the administered PANAS versions.

Markov Chain Model in FE Dynamics In this study, the MC-inspired approach described in section 2.7 was adopted specifically tailored to the continuous emotional space generated by the WAFER system. Following Ekman’s emotion taxonomy [136, 138], each time point is represented by a 7-dimensional probability vector associated with the canonical FEs (*angry, disgust, fear, happy, neutral, sad, surprise*). To characterise emotion transitions, TCMs are constructed by accumulating outer products of consecutive FE vectors. The resulting TCMs for both the Snake and the Matching Pairs games summarise the temporal evolution of each subject’s emotional profile throughout the full task. From this continuous-state operator for each individual in both Snake and Matching Pairs games, a total of ten standard Markov metrics are calculated (section 2.7).

HRV and Related Features HRV analysis was performed starting from ECG recordings at different sample frequencies, depending on the population group: $f_s = 250Hz$ for Korean and Japanese cultural groups and $f_s = 300.62Hz$ for the Italian cultural group. ECG preprocessing included bandpass filtering to remove noise and baseline wander, followed by R-peak detection using the Pan-Tompkins algorithm [336, 390], previously described in subsection 2.5.1. Once R-peaks were identified, the RR intervals were extracted, forming a sparse time series due to the non-uniform nature of cardiac rhythms. To obtain a continuous and analytically tractable representation of HRV, the RR interval time series was interpolated using the point process model developed by Barbieri et al. [30], as described in subsection 2.5.2. The point process algorithm finally provided a uniformly sampled HRV signal ($f_s = 50Hz$) suitable for standardizing the feature extraction process across all subjects and performing subsequent analysis. HRV metrics were then computed across multiple domains: (i) time-domain features, (ii) frequency-domain metrics derived through spectral decomposition (Welch’s method) to quantify power distribution across very-low-frequency (VLF), low-frequency, and high-frequency bands, (iii) entropy-based measures (approximate, sample, and distribution entropies), (iv) fractal and scale-free metrics, and (v) RQA-derived metrics to characterize the complexity and dynamical properties of heart rate fluctuations. As previously reported, sep-

arate GLMMs were estimated for the identified two HRV feature groups to analyse the data in a progressive complexity framework. The 'canonical' HRV metrics group, encompassing features from domains (i)–(iii), represents the first level of analysis, reflecting linear and physiologically established aspects of autonomic variability. Once this baseline level was characterised, a second GLMM was fitted for HRV features belonging to domains (iv) and (v), which reflect a higher level of dynamical and structural complexity in the RR series.

4.4.4 Results

Results of Step Ia

The GLMM analysis of FE dynamics activation across Italian, Japanese, and Korean cultural groups during gameplay revealed distinct cultural patterns. The results showed that the Italian cultural group generally exhibited lower activation levels for negative FE, such as *angry* and *disgust*. In contrast, participants from Japanese and Korean cultural groups showed higher activation levels for these emotions. *Fear* was more prominent among Italians and Koreans cultural groups, with Japanese culture participants showing lower activation.

Happy was highly activated in the Italian culture group but was game-dependent for Japanese cultural group and notably low among the Korean culture group. *Neutral* FE activation also varied based on the game for all cultures. *Sad* was low for participants from Italian and Japanese cultural groups but highly activated among participants from the Korean culture group. Lastly, *surprise* was more frequently observed in the Italian culture group, whereas it was less pronounced in the Japanese and Korean culture groups. The Korean culture group served as the reference group throughout the analysis. Table 4.3 shows a detailed analysis of Snake game and Matching Pairs game between different cultural groups. The detailed analysis of FE during the Matching Pairs and the Snake game provides a deeper insight into these general patterns: For the *angry* FE, Italian cultural group showed a significantly lower activation probability ($\beta = -3.83, t = -14.78^{***}$) during the Matching Pairs game. Moreover, Japanese cultural group showed a significantly higher activation probability ($\beta = 2.05, t = 9.12^{***}$). For the Snake game, Italian cultural group again showed a significantly lower activation probability ($\beta = -3.24, t = -19.17^{***}$), while Japanese cultural

Table 4.3: FE Analysis by Country for Matching Pairs Game and Snake Game. F denotes the overall model F-statistic testing whether the regression model explains a significant proportion of variance in the dependent variable, β indicates the estimated regression coefficient representing the strength and direction of the relationship between variables and t is the corresponding t-statistic assessing the significance of each coefficient. *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

Emotion	Country	Matching Pairs Game			Snake Game		
		F	β	t	F	β	t
Angry	Italy	264.7***	-3.83	-14.78***	278.41***	-3.24	-19.17***
	Japan		2.05	9.12***		0.42	2.71**
	Korea		Ref.	-		Ref.	-
Disgust	Italy	21.4***	-0.11	-6.47***	19.02***	-0.15	-4.36***
	Japan		-0.03	-2.07*		0.05	1.70
	Korea		Ref.	-		Ref.	-
Fear	Italy	82.0***	-0.02	0.38	120.58***	-0.01	0.11
	Japan		-0.58	-11.27***		-0.40	-13.52***
	Korea		Ref.	-		Ref.	-
Happy	Italy	139.9***	5.66	16.66***	50.07***	3.70	7.84***
	Japan		2.59	8.79***		3.95	9.24***
	Korea		Ref.	-		Ref.	-
Neutral	Italy	39.4***	1.21	2.44*	16.11***	2.87	5.58***
	Japan		3.75	8.72***		1.68	3.61***
	Korea		Ref.	-		Ref.	-
Sad	Italy	456.4***	-7.50	-24.37***	483.02***	-7.11	-28.23***
	Japan		-7.18	-26.89***		-5.74	-25.09***
	Korea		Ref.	-		Ref.	-
Surprise	Italy	428.0***	4.54	24.25***	381.43***	3.95	24.26***
	Japan		-0.61	-3.75***		0.04	0.24
	Korea		Ref.	-		Ref.	-

group showed a smaller yet still significantly higher activation probability ($\beta = 0.42$, $t = 2.71^{**}$).

For the *disgust* FE cluster, during the Matching Pairs game, Italian cultural group showed a slightly lower activation probability ($\beta = -0.11$, $t = -6.47^{***}$), while Japanese cultural group also showed a lower activation probability ($\beta = -0.03$, $t = -2.07^*$), although less pronounced than the Italian cultural group. In the Snake game, the Italian cultural group continued to show lower activation probability ($\beta = -0.15$, $t = -4.36^{***}$). In contrast, the response of the Japanese cultural group was not significant ($\beta = 0.05$, $t = 1.70$).

The analysis of *fear* FE revealed a different pattern. In the Matching Pairs game, the Italian cultural group showed no significant change in *fear* FE ($\beta = -0.02$, $t = 0.38$). In contrast, Japanese cultural group exhib-

Table 4.4: p -values resulting from statistical analysis to distinguish between high-scoring and low-scoring players at the Snake and Matching Pairs games, along with descriptive statistic parameters (median and iqr). *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

Game / Feature	ER	St	SpG	MHT Angry	MHT Disgust	MHT Fear	MHT Happy	MHT Neutral	MHT Sad	MHT Surprise
Snake p -value	1.3×10^{-3} *	0.16	0.09	0.96	0.16	0.34	3.2×10^{-2} *	5.4×10^{-3} *	0.89	0.49
Snake median _{high-scoring}	0.85	0.15	0.97	48.82	697.30	517.70	61.90	1.06	14.89	78.96
Snake iqr _{high-scoring}	0.39	0.04	0.19	113.94	1054.23	657.55	155.14	0.16	22.64	158.90
Snake median _{low-scoring}	1.05	0.16	0.90	57.24	588.36	368.57	20.36	1.28	13.70	67.13
Snake iqr _{low-scoring}	0.54	0.04	0.24	110.88	941.61	985.56	99.96	0.48	26.03	162.30
Matching Pairs p -value	0.42	0.08	1.7×10^{-2} *	0.27	0.19	0.14	8.1×10^{-3} *	0.91	0.21	4.1×10^{-2} *
Matching Pairs median _{high-scoring}	0.91	0.15	0.99	46.51	859.94	572.10	388.48	1.08	11.59	139.52
Matching Pairs iqr _{high-scoring}	0.43	0.01	0.03	95.60	970.47	1165.34	971.60	0.29	20.80	588.80
Matching Pairs median _{low-scoring}	0.92	0.15	0.98	37.56	621.06	371.54	70.19	1.06	12.77	55.87
Matching Pairs iqr _{low-scoring}	0.54	0.01	0.05	98.81	922.07	718.45	275.77	0.25	24.60	136.28

ited a statistically significant lower activation probability ($\beta = -0.58$, $t = -11.27^{***}$). During the Snake game, Italian cultural group also showed no significant activation ($\beta = -0.01$, $t = -0.11$), but Japanese cultural group showed a marked lower activation probability in *fear* FE ($\beta = -0.40$, $t = -13.52^{***}$).

The *happy* FE cluster showed a highly increased activation probability in Italian cultural group during the Matching Pairs game ($\beta = 5.66$, $t = 16.66^{***}$), with Japanese cultural group also showing a significantly higher activation probability ($\beta = 2.59$, $t = 8.79^{***}$). In the Snake game, both Italian ($\beta = 3.70$, $t = 7.84^{***}$) and Japanese cultural group ($\beta = 3.95$, $t = 9.24^{***}$) continued to show significantly higher activation probability compared to Korean cultural group.

The *neutral* FE activation varied by game. During the Matching Pairs game, Italian cultural group participants showed a modestly higher activation probability ($\beta = 1.21$, $t = 2.44^*$), with Japanese cultural group showing a more significant response ($\beta = 3.75$, $t = 8.72^{***}$). In the Snake game, both Italian ($\beta = 2.87$, $t = 5.58^{***}$) and Japanese cultural group ($\beta = 3.18$, $t = 5.87^{***}$) exhibited significantly higher activation probability.

For *sad* FE, Italian cultural group showed a strong lower activation probability during the Matching Pairs game ($\beta = -7.50$, $t = -24.37^{***}$), and this trend continued in the Snake game ($\beta = -7.11$, $t = -28.23^{***}$). Japanese cultural group similarly showed substantial lower activation probability ($\beta = -7.18$, $t = -26.89^{***}$) in the Matching Pairs game and ($\beta = -5.74$, $t = -25.09^{***}$) in the Snake game.

Lastly, in the case of *surprise* FE, Italian cultural group showed significantly higher activation probability during both the Matching Pairs ($\beta = 4.54, t = 24.25^{***}$) and the Snake ($\beta = 3.93, t = 24.26^{***}$) games. In contrast, the Japanese cultural group showed a significantly lower activation probability in the Matching Pairs game ($\beta = -0.61, t = -3.75^{**}$) and no significant activation difference in the Snake game ($\beta = 0.04, t = 0.24$).

Results of Step Ib

Statistical analysis was performed to detect differences among the characteristic features of the TCMs across different cultures in the Snake and Matching Pairs games. Since the Shapiro-Wilk normality test (significance level $\alpha = 0.05$) rejected the null hypothesis for all features' distribution, the non-parametric Kruskal-Wallis test (significance level $\alpha = 0.05$) was implemented to test whether MC-related features of FE dynamics belonging to different cultures come from the same distribution. A post-hoc Tukey-Kramer correction was used to test multiple comparisons. Figure 4.12 and Figure 4.13 summarise all significant cultural differences in MHTs.

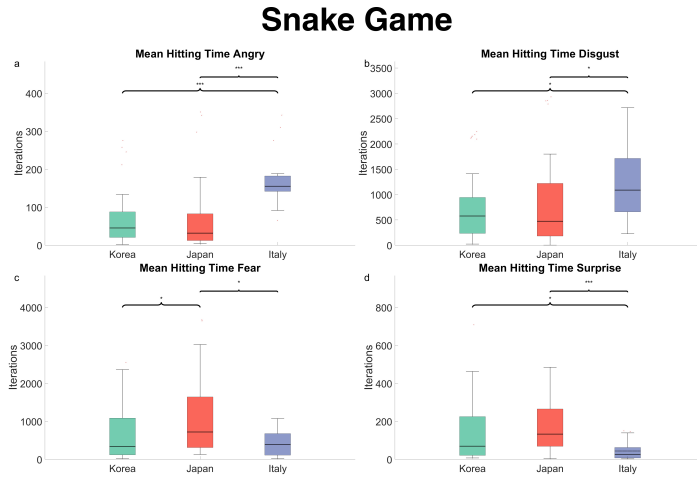


Figure 4.12: Significant comparisons resulting from MC analysis on FE data across different cultures in the Snake game. *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

In the Snake game (Figure 4.12), cultural effects emerged for the *an-*

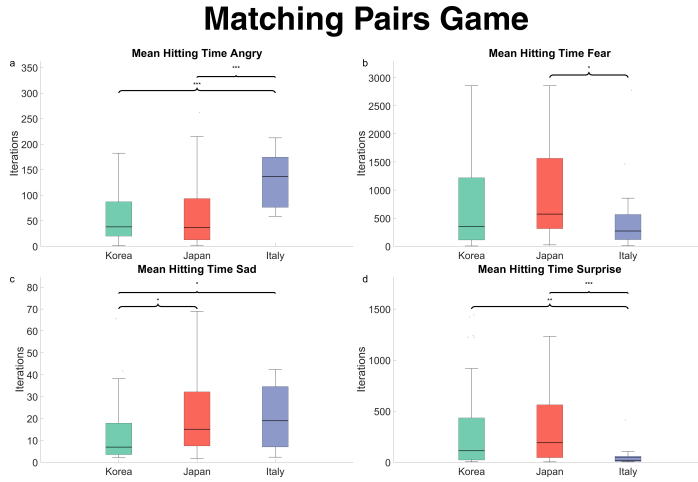


Figure 4.13: Significant comparisons resulting from MC analysis on FE data across different cultures in the Matching Pairs game. *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

gry, *disgust*, *fear* and *surprise* MHTs. For the *angry* FE, the Italian cultural group showed higher MHTs than both the Korean ($p < .001$) and the Japanese ($p < .001$) cultural groups; the associated effect size reflected a strong divergence across cultures ($d = 1.022$). For the *disgust* FE, the Italian cultural group again exhibited higher MHTs ($d = 0.487$) than both the Korean ($p < .05$) and the Japanese ($p < .05$) cultural groups. The *fear* FE condition showed a different configuration: Japanese cultural group displayed the highest MHTs with respect to Korean ($p < .05$) and Italian cultural group participants ($p < .05$, $d = 0.613$). Finally, for the *surprise* FE, both Korean ($p < .05$) and Japanese ($p < .001$) cultural groups showed higher MHTs, while Italians appeared faster and more consistent in their responses ($d = 0.82$). A similar pattern was found in the Matching Pairs game (Figure 4.13), where cultural modulation of MHTs was again evident across several emotional states. For the *angry* FE, the Italian cultural group confirmed their markedly higher MHTs compared to both the Korean ($p < .001$) and the Japanese cultural group ($p < .001$, $d = 0.868$). A similar pattern, though less pronounced with respect to the Snake game, was observed for the *fear* FE, where the Japanese cultural group displayed higher MHTs relative to their Italian counterparts ($p < .05$, $d = 0.467$). For the *sad* FE,

the Korean cultural group generally exhibited the lowest MHTs, while the Japanese ($p < .05$) and Italian ($p < .05$) cultural groups showed higher values ($d = 0.58$). Finally, for the *surprise* FE, the Italian cultural group confirmed the trend demonstrated in the Snake game by displaying the lowest MHTs, whereas both the Korean ($p < .01$) and Japanese ($p < .001$) cultural groups showed consistently higher values ($d = 0.863$). No significant differences, in terms of MHTs, were observed for the *neutral* and *happy* FEs for both games.

Furthermore, PANAS mean scores were examined in relation to participants' performance, specifically evaluating their trends before and after both games. The statistical results of this analysis, obtained by performing the Mann-Whitney U-test, are summarized in section A.2, Figure A.4. Notably, high-performing players in the Snake game exhibited lower negative emotions both before ($p = .0265$, $d = 0.633$) and after ($p = .0161$, $d = 0.693$) gameplay, as well as increased positive emotions post-game ($p = .0351$, $d = 0.599$), compared to lower-performing participants. A similar trend was observed for the Matching Pairs game, where higher-performing individuals showed an increase in positive emotions after gameplay ($p = .0257$, $d = 0.637$). Subsequent analyses then explored differences in MC-related features between high-scoring and low-scoring individuals for both Snake and Matching Pairs games. Shapiro-Wilk normality test (significance level $\alpha = 0.05$) rejected the null hypothesis for all features' distribution, so the non-parametric Mann-Whitney U-test (significance level $\alpha = 0.05$) was used for statistical comparisons. The results are briefly reported in Table 4.4, along with descriptive statistic parameters (median and interquartile ranges) for high-scoring and low-scoring players in Snake and Matching Pairs games. Statistical analysis results for significant comparisons are also reported as boxplots (see section A.2, Figure A.5 and Figure A.6). Substantially, low-scoring players in the Snake game show lower MHT for the *happy* FE ($d = 0.691$) and higher MHT for the *neutral* FE ($d = 0.856$). Also, low-scoring players exhibit higher ER values with respect to high-scoring players ($d = 1.023$). In the Matching Pairs game, instead, high-scoring players have higher SpG ($d = 0.707$) with respect to low-scoring ones and also exhibit higher values for the *happy* ($d = 0.883$) and *surprise* ($d = 0.618$) FEs.

Lastly, the comparison of MC-related features across Snake and Matching Pairs games for all participants. Shapiro-Wilk normality test confirmed non-Gaussian distribution of data; therefore, the Mann-Whitney U test (sig-

nificance level $\alpha = 0.05$) was used for statistical analysis. Results, reported in section A.2, Figure A.7, show higher St values for the Snake game ($p < .001$, $d = 0.816$), whereas in the Matching Pairs game, the SpG is larger ($p < .001$, $d = 1.071$). Also, the two video games differ for the *happy* FE, which is less prominent in the Matching Pairs game with respect to the Snake game ($p < .01$, $d = 0.478$) and, therefore, tends to have a later onset (in terms of MHT: $p < .001$, $d = 0.891$) in the emotional space of players.

Results of Step II

All GLMM results related to Step II are shown in Table 4.5. GLMMs results on the Snake game indicate that both sets of HRV features are significantly related to task performance. However, the combined model provided the best fit, with the lowest AIC and BIC values, and achieved the highest R^2_{cond} (0.912). The significance of features encompassing both FE and HRV domains (WAF_ST, WAF_SPG, pNN50) suggests that incorporating multiple physiological features provides a more comprehensive representation of cognitive engagement during the Snake game.

GLMMs' results on the Matching Pairs game showed that HRV features significantly predicted task performance, particularly time-domain and entropy-related measures. The highest R^2_{cond} (0.687) was observed in the HRV 'complex' model, while the combined model did not show a substantial improvement in R^2_{cond} (0.655). This suggests that adding additional physiological metrics beyond the HRV 'complex' feature set did not necessarily enhance the model's predictive power. However, the combined model still provided the best overall fit based on AIC and BIC values, indicating a more balanced trade-off between complexity and explanatory power. Conversely, in the Snake game, no FE-related features were significant in the combined model.

The combined models for both games highlight the significant features influencing task performance. The Snake game demonstrated the highest predictive power across all features combined ($R^2_{cond} = 0.912$). In contrast, the Matching Pairs game showed that the HRV 'complex' feature set alone accounted for most of the variance in performance ($R^2_{cond} = 0.687$). These results suggest that HRV-derived features, particularly those linked to entropy and recurrence patterns, play a crucial role in modulating cognitive performance during game tasks.

Table 4.5: GLMMs results for the Snake and the Matching Pairs games, with indications on the number of subjects included/excluded in each model, values of AIC, BIC and R^2_{cond} . Significant fixed effects are reported along with direction (+ = positive, - = negative) and level of significance (*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$).

GAME / Feature Set	Included/Excluded	Significant Fixed Effects	AIC	BIC	R^2_{cond}
<i>SNAKE GAME</i>					
FE Feat.	-	-	-	-	-
HRV 'canonical' Feat.	105 / 4	pNN50* (-), ApEn*** (+), SampEn2*** (-), DistEn* (-)	21,09	25,725	0,874
HRV 'complex' Feat.	105 / 4	RR* (-), mean RT** (+), max RP path length* (+)	129,104	134,059	0,872
Combined	101 / 8	WAF.ST** (+), WAF.SPG** (+), pNN50* (-)	-7,552	-3,688	0,912
<i>MATCHING PAIRS GAME</i>					
FE Feat.	-	-	-	-	-
HRV 'canonical' Feat.	107 / 2	meanRR** (-), RMSSD* (+), TriRR* (+), stdDER1** (-), ApEn*** (-), SampEn2*** (+)	-69,906	-65,218	0,639
HRV 'complex' Feat.	107 / 2	mean RT** (+), max RP length** (-), TT* (-)	-7,045	2,045	0,687
Combined	94 / 15	meanRR* (-), mean RT* (+), max RP length* (-), TT* (-)	-89,346	-85,777	0,655

4.4.5 Discussion

The universality of FEs has been widely discussed, results from Jack et al. [210] demonstrate that facial configurations might not be culturally uniform. Following their results, Eastern observers tend to rely more on eye-region cues and exhibit less distinct clustering of basic emotions than Western observers. Such findings highlight that cultural norms shape how facial movements are produced and perceived. Consequently, cultural variability also has technical implications for ML and FER. CNN-based systems may show lower accuracy when trained on datasets that do not sufficiently represent diverse cultural facial movement patterns. This issue becomes clear when considering the datasets commonly used in the field, since multicultural datasets such as RAF-DB [270,271] and AffectNet [312] exist alongside single-culture datasets such as JAFFE [279,280]. The choice of these datasets and methodology determines how culturally sensitive and generalisable the resulting FER models can be.

Emotions are at the root of the human experience, shaping decision-making [266], social interactions [287], and overall well-being [421]. They serve as important indicators guiding individuals in managing complex social environments and responding to their daily challenges. The nature of human emotions is inherently dynamic and multifaceted, encompassing both action-oriented and inhibition-oriented forms of negative emotional activation. Emotions such as *angry* and *disgust* are typically associated with an

action-oriented response. *Angry*, in particular, as an emotion, is highly associated with a sense of empowerment, leading individuals to confront and challenge perceived injustices, thereby encouraging proactive behaviour and collective action for groups [308]. The association of *angry* and behaviour is so clear that some researchers have argued that it is almost self-evident, reflecting the natural tendency of anger to lead individuals to respond forcefully to threats or challenges [238,308]. Similarly, *disgust*, although primarily a response to objects or actions perceived as harmful or repulsive, often elicits a strong drive to eliminate or distance oneself from the source, thereby reinforcing active interaction with the environment and individuals [140, 333, 365]. In addition, moral *disgust*, a type of *disgust* elicited by violations of moral or ethical norms, is correlated with anger, further emphasizing its role in driving action-oriented responses [293,397].

In contrast, emotions such as *fear* and *sad* are more likely to lead to inhibition or disempowerment, resulting in passive or avoidant behaviour. *Fear*, for instance, is associated with avoidance rather than confrontation, leading individuals to withdraw from the perceived source of danger [281, 308, 364]. Furthermore, anxiety-realized *fear* can trigger a 'freeze' response, where the individual becomes unable to act or move, reflecting a more extreme form of passivity in the face of threats [383]. Likewise, *sad*, which is often associated with a sense of loss and lack of action, is typically characterized by passivity and a general slowing of the body, reducing motivation to action [21,415].

Static Patterns of FEs Across Cultures The Step Ia provides a broad, static overview by examining how the WAFER system detects FE across cultures during gameplay, establishing general cross-cultural patterns in outward emotional expression. Studies in the literature have consistently shown that culture plays a crucial role in influencing both emotional experiences and how these emotions are represented [134,139,296]. Furthermore, the degree to which these FE are displayed may also vary across cultures [296]. In this context, three hypotheses were formulated to strengthen the study. The first of these hypotheses (*H1.1*) was "*Italian cultural group is expected to exhibit a higher probability of happy FE and a lower level of negative FE compared to Japanese and Korean cultural groups while playing Snake and Matching Pairs games*". Results indicated that the Italian cultural group exhibited a higher probability of *happy* FE and a lower level of negative FE, thereby supporting H1.1 (see β values in Table 4.3). Following the literature,

Italian culture stands out among European cultures for its unique emphasis on pleasure and enjoyment, deeply rooted in its historical and cultural roots [159]. This hedonic form of cultural orientation [159] significantly affects various aspects of life, including motivations related to leisure activities, such as video games. Moreover, another study reports that 'entertainment' is a key reason people play video games, with Italian gamers dominating this aspect [181].

The second hypothesis (*H1.2*) was, "*Japanese cultural group is expected to be less likely to show fear FE compared to Italian and Korean cultural group while playing Snake and Matching Pairs games*". Results showed that the Japanese cultural group exhibited lower levels of *fear* of FE compared to the other groups, leading to the acceptance of *H1.2* (see β values in Table 4.3). These findings are consistent with the existing literature and can highlight how cultural norms shape FE in video game contexts. Moreover, in individualistic cultures, particularly in the West, authenticity is highly valued in various aspects of life [62]. However, in collectivist cultures, such as Japan, greater emphasis is placed on conforming one's behaviour to social expectations and avoiding inappropriateness [72]. This often involves "masking" emotions, a practice particularly evident in Japan's status-conscious society, where individuals tend to suppress expressions of *fear* [106]. Furthermore, cultural values such as fearlessness, integrity, and bravery are deeply rooted in Japanese traditions, such as Bushido and Buddhism [114]. These cultural values may have shaped the social norms surrounding emotional expression [113]. Although these philosophies do not explicitly mandate the suppression of *fear*, they have influenced the implicit rules of emotional display and may act as moderating factors in emotional regulation [298].

The third hypothesis (*H1.3*) was "*Korean cultural group is expected to be more likely to show negative FE compared to Italian and Korean cultural group while playing Snake and Matching Pairs games*". Findings highlighted that Korean participants expressed a higher frequency of negative FE, which supports *H1.3* (see β values in Table 4.3). The findings from the literature are consistent with the *H1.3* results regarding FE in the Korean cultural group. For instance, Koreans are known to often show negative emotions, both verbally and non-verbally, in response to a variety of social and personal stimuli. Studies by M. Kim [226, 227] and Y. Kim [229] indicate that emotions such as *sad*, *angry*, *disgust*, and *shame* are frequently experienced, especially in circumstances involving personal failure, interpersonal betrayal,

or interactions with people perceived as morally corrupt [391]. This tendency may be associated with the competitive dynamics inherent in Korean society, where individuals often face significant expectations and pressure to achieve success [410, 414]. In this context, competition (whether in academic settings, career advancement, or social interactions) can trigger frustration and heighten sensitivity to failure. Consequently, it can result in more negative emotional expressions than in other cultures.

Dynamic Evaluation of FEs Across Cultures This step investigated the dynamic space of players' FE profiles, assessing how cultural background, emotional processing, cognitive performance, and game type shaped the timing of emotional responses. In Step Ib, the analysis focused on the continuous-state Markov operator derived from FE probabilities and, in particular, on the MHT. This metric provided a temporally resolved characterisation of emotional transitions that complements the static effects identified in Step Ia. Whereas the GLMM analysis quantified the extent to which each FE was activated, the MHT captured how quickly each emotion emerged during gameplay, revealing systematic differences across cultural groups, game types, and performance levels. Here, cultural differences were investigated, testing whether groups from distinct cultural contexts showed statistical significant different temporal patterns in the MHT measure. Interestingly, cross-cultural variations emerged across both games.

In the Snake game (Figure 4.12), Italian cultural group displayed delayed expressions of negative-valence emotions, particularly *angry* and *disgust* (Figure 4.12a,b), compared with the Korean and Japanese cultural groups. At the same time, the Italian cultural group showed a faster onset of *surprise* (Figure 4.12d), suggesting heightened reactivity to unexpected events in this fast, dynamic task. The Japanese cultural group exhibited a consistent delay in *fear* (Figure 4.12c), confirming the pattern already noted in Step Ia and aligning with culturally shaped tendencies to modulate the expression of this emotion. Korean cultural group, by contrast, showed relatively shorter and more uniform MHT, indicating more stable expressivity across conditions. In the Matching Pairs game (Figure 4.13), similar cultural patterns were observed, but with a structure that reflects the task's slower, memory-oriented nature. Italian cultural group showed later *angry* and *sad* responses (Figure 4.13a,c), yet their *fear* and *surprise* responses were now faster than those of the Japanese cultural group (Figure 4.13b,d), whose *fear*

delay persisted across tasks (Figure 4.13b). Koreans maintained comparatively rapid and consistent MHT, reinforcing their stable emotional response profile.

Moreover, these findings suggest that cultural background meaningfully shapes not only the intensity but also the timing and trajectory of emotional expressions during gameplay [210]. Importantly, the direction and magnitude of these differences depend on the task’s cognitive and emotional demands [195]. The Snake game, characterized by speed, uncertainty, and continuous threat detection, amplifies cross-cultural differences in rapid-reactivity emotions [260, 457]. In contrast, the Matching Pairs game relies on memory load, anticipation, and slower decision cycles, thereby highlighting cross-cultural differences in more deliberate or expectation-driven emotional responses. These observations are consistent with models distinguishing fast vs. slow emotional processes, i.e., rapid, reactive emotions emerge predominantly in time-pressured contexts. In contrast, slower, cognitively mediated responses are more evident in tasks requiring memory, planning, or sustained attention [347].

Complementary analyses on PANAS scores align with the existing literature [215], indicating that higher-performing players experience greater activation of positive emotions after the game sessions (see Figure A.4 in section A.2). Building on these self-reported differences, the investigation focused on whether such affective patterns were also observable at the level of behavioral emotion dynamics, assessing whether cognitive task performance was reflected in differences in the MHTs of players’ FEs, comparing how these emotion-specific durations vary between high- and low-scoring players. Notably, the faster transition to *happy* in low-scoring players may not indicate true positive affect but rather a reactive or involuntary emotional response, such as nervous laughter or smiling immediately after making a mistake [237]. Such expressions can serve as brief emotional releases or coping mechanisms under stress, as commonly observed in performance-failure situations [237]. Moreover, low-scoring players also demonstrated higher ER values in the Snake game. As ER reflects the unpredictability of transitions between emotional states, this increased variability in low-scoring players may indicate less consistent or more chaotic emotional regulation, potentially undermining their cognitive performance under pressure. Conversely, in the Matching Pairs game, high-scoring players showed higher SpG values, suggesting their emotional state transitions stabilize more rapidly. In the

context of MC modeling, a larger SpG signifies a faster convergence to a steady emotional pattern, an attribute that may support sustained attention and better decision-making. Additionally, high-scoring players in the Matching Pairs game exhibited higher MHTs for the *happy* and *surprise* expressions, implying a more prolonged trajectory to these states. This may reflect a more controlled or deliberate emotional response, possibly indicative of better cognitive engagement and focus. These findings suggest that FER-derived MC metrics can meaningfully differentiate emotional processing styles linked to performance levels. High-scoring players tend to exhibit more stable and structured emotional dynamics traits, likely conducive to better cognitive control and game performance. In contrast, low-scoring players appear to experience more volatile and less regulated emotional patterns, which may hinder cognitive efficiency.

Finally, it was investigated if the type of game influenced the dynamics of players' FEs. The MC model-based analysis showed greater emotional stability between consecutive states in Snake compared to Matching Pairs, and the emotional space available for exploration in Snake was more limited than in Matching Pairs. This reduction in emotional space, combined with increased stability, can be interpreted as a way to focus more on the game itself. Additionally, in the Snake game, there was a higher prevalence of positive emotions (i.e. *happy*), both in terms of presence and latency, according to Ferro et al. [151], which reported that the positive emotions experienced by gamblers do not show differences between the different types of games, as these seem more linked to a more internal connection with the game.

Combining FE and HRV Data to Model Gameplay Performance

GLMM analysis of the Snake and Matching Pairs games reveals profound insights into the interactions among FE, "canonical," and "complex" HRV feature sets in predicting cognitive outcomes. For the Snake game, FE features alone could not predict performance; however, both HRV feature sets demonstrated strong explanatory power, as evidenced by high R^2_{cond} values (Table 4.5). Among these, entropy measures (ApEn, SampEn, and DistEn) and RQA-derived features (recurrence rate, mean recurrence time, and max recurrence plot path length) stood out as significant fixed effects (Table 4.5). These findings underscore the intricate relationship between cardiovascular dynamics and cognitive processes, emphasizing the role of autonomic regulation in shaping task performance. The integration of FE and HRV features

for the Snake game significantly enhanced the R^2_{cond} , reaching a value of 0.912 (Table 4.5). In this combined model, FE-related features (WAFERSt and WAFERSpG) emerged as significant predictors alongside pNN50 from the 'canonical' HRV features set (Table 4.5). The inclusion of pNN50, a time-independent HRV measure, confirms its robustness as a marker of cognitive performance. A recent study on stress and cognitive performance found that reduced HRV, as measured by pNN50, was associated with better performance under stress. High-performing individuals showed greater parasympathetic recovery after stress, which could be linked to their ability to maintain performance under pressure [311]. These results point to the critical role of emotional and cardiovascular markers in understanding cognitive load, revealing a dynamic interplay between emotional states, autonomic regulation, and task demands, as changes in HRV, particularly in the context of mental stress, have already been linked to changes in cognitive load and emotional states [304]. Such findings raise pivotal questions about the modulation of cardiovascular activity during video gameplay, particularly regarding how shifts in sympathovagal balance, as captured by HRV and FE data, reflect cognitive engagement and adaptability across varying task conditions. For the Matching Pairs game, a similar analytical framework was employed. Even for the Matching Pairs game, GLMM analysis relying solely on FE-related features was insufficient for predicting cognitive outcomes, while 'canonical' and 'complex' HRV domains yielded significant insights (Table 4.5). Time-domain (meanRR, RMSSD, TriRR, and stdDER1) and entropy-related measures (ApEn and SampEn) from the 'canonical' HRV feature set, along with RQA metrics (mean recurrence time, max recurrence plot path length, and trapping time) from the 'complex' HRV feature set, emerged as pivotal predictors (Table 4.5). These results solidify the relevance of advanced HRV analyses in assessing cognitive performance, particularly in tasks requiring sustained attention and cognitive stability [155]. Interestingly, the combined GLMM for the Matching Pairs game did not improve the R^2_{cond} , which remained at 0.655 (Table 4.5). Despite this, the importance of RQA-derived features (mean recurrence time, max recurrence plot path length, and trapping time) and meanRR was reaffirmed (Table 4.5). This suggests that while FE metrics played a less prominent role in the Matching Pairs game, autonomic markers reflecting recurrent and stable patterns were critical for understanding task-related performance. These findings provide compelling evidence for the role of autonomic dynamics in characterizing

cognitive load [173], with features like meanRR and entropy measures serving as robust markers of task-specific physiological regulation. The results underscore the broader impact of cardiovascular activity modulation during gameplay, revealing task-specific patterns of autonomic regulation and emotional engagement [433]. For the Snake game, the interplay between recurrent autonomic patterns and emotional stability highlights the importance of adaptive sympathovagal balance in navigating cognitively demanding tasks. Conversely, the Matching Pairs game's reliance on stable autonomic markers suggests a need for consistent cognitive focus and physiological steadiness. These distinctions have profound implications for understanding how autonomic dynamics and emotional states shape cognitive performance in interactive and high-stakes environments. From a translational perspective, these findings have significant potential for informing the design of interventions and adaptive technologies. By leveraging the interplay between cardiovascular activity and emotional markers, it may be possible to develop personalized gaming or training platforms that optimize cognitive performance and emotional resilience. Furthermore, integrating these insights into real-world applications, such as neurorehabilitation and cognitive training programs, could pave the way for innovative strategies to enhance neuroplasticity, functional connectivity, and overall cognitive health.

4.4.6 Implications, Future Studies and Limitations

The outcomes of this study provide important insights for game designers, who can use these findings to create more engaging and culturally immersive gaming experiences. By understanding how emotions are expressed differently across cultures, designers can adapt game elements to appeal more to different players, increasing both entertainment and immersion. Emotions, especially negative ones, are crucial in shaping players' experiences. Thus, the emotional impact of a game goes beyond its content and extends to how it triggers emotions; this study provides a basis for considering these factors within regulatory frameworks for game design, potentially guiding industry standards for how games manage emotional responses. In addition, the biosignal findings have practical implications for performance-oriented activities such as eSports, where emotional regulation and physiological responses directly affect player performance. Incorporating these findings into training and game design could help foster better mental resilience and control, leading to improved outcomes in competitive settings.

Future studies could benefit from including a wider range of cultural groups to deepen the understanding of how emotional expressions and experiences during gameplay differ across cultural backgrounds. By including participants from different regions, researchers may uncover more complex and culturally specific responses. In addition, expanding the physiological measures to include EEG and Photoplethysmography data could provide a more comprehensive view of players' emotional and physiological states, complementing existing FE data. Integrating eye-tracking technology with advanced FE recognition systems would further refine emotional assessments, enabling more accurate interpretation of participants' reactions during gameplay. This multimodal approach could lead to a deeper understanding of the interactive dynamics between cultural factors, physiological responses, and emotions in gaming contexts.

Moreover, future studies could also consider the natural characteristics of emotion datasets, as emotions such as happiness are often more easily repeatable than others. This tendency, which is commonly observed across multiple datasets in the literature, may contribute to distributional imbalances. Addressing such dataset-related issues through augmentation or resampling techniques could further strengthen the robustness of future findings.

There are several limitations to this study. First, using only two casual video games may limit the range of emotions elicited in participants, because casual games generally evoke less intense emotional responses than more complex and immersive games. This limitation is particularly relevant for emotions such as disgust and fear, which typically emerge in richer contexts that contain stronger narrative, threat-related, or sensory cues. Consequently, these findings may not be generalizable to other video games. Nevertheless, this study represents an initial step in examining cross-cultural differences in emotional and physiological responses. The use of casual, comparable games provided a controlled setting for this initial exploration. Taken together, these considerations may also help explain why the features of FEs were not predictive of performance. Future research should include more complex game genres to assess whether similar patterns emerge when emotions are elicited under greater cognitive and emotional demands.

A methodological limitation of the present work is associated with the adopted Markov-inspired approach. The transition operator was derived from continuous FE probability vectors rather than from strictly discrete emotional states. As a result, the model should be interpreted as a Markov

process over probabilistic emotional profiles, rather than as a classical finite-state emotion MC. This continuous-state formulation is well suited to the graded nature of FE outputs and allows for a principled characterisation of temporal dependencies, but future research could compare this approach with models based on discrete emotional labels or on clustered latent states to evaluate potential differences in interpretability and sensitivity.

In addition, the emotion recognition model used is inherently a 'black box', meaning that its internal processing is not easily interpretable. This lack of transparency makes it difficult to fully understand how the model detects and classifies emotions from FEs, potentially limiting insight into specific emotional nuances that vary across cultures. Lastly, the interpretation of the emotion surprise is inherently context-dependent. Unlike emotions with clear positive or negative valence, such as happiness or sadness, surprise can emerge in response to both pleasant and unpleasant situations, including happy achievements or sudden failures. This contextual variability makes it more difficult to consistently categorize surprise. As a result, FE recognition systems may struggle to accurately interpret surprise, potentially overlooking the emotional nuance conveyed by the expression. This limitation is especially relevant in cross-cultural settings, where similar FEs of surprise may convey different meanings based on cultural norms and situational expectations.

4.5 Conclusions

This chapter investigated psychophysiological engagement during interactive, goal-directed digital games, positioning game-based tasks as an intermediate level of complexity between highly controlled laboratory tasks and fully naturalistic real-world settings. Building on the foundational analyses of basic stimulus-driven responses presented in earlier chapters, the focus here shifted toward active human-computer interaction, where cognitive load, emotional activation, and autonomic regulation continuously evolve in response to task demands and performance. Across three complementary studies, the chapter demonstrated that even simple casual games can elicit structured and measurable modulations across central, autonomic, behavioral, and affective domains. Importantly, these modulations were not static outcomes but dynamic processes unfolding over time, shaped by the interaction between task structure, individual performance, and contextual factors.

Findings confirm that game-based paradigms offer a valuable methodological compromise, retaining experimental control while enabling the investigation of engagement as an emergent, time-varying phenomenon. A central contribution of this chapter lies in showing that engagement during gameplay cannot be reduced to a single physiological or psychological marker. The EEG study highlighted how sustained performance in a continuous visuomotor task is supported by adaptive neural regulation, whereas reduced performance is associated with signatures of cognitive overload and diminished attentional efficiency. The pupillometry study, in turn, revealed that autonomic markers can capture subtle differences in cognitive resource allocation even when subjective affective reports remain largely unchanged. Finally, the cross-cultural multimodal study demonstrated that emotional expression, autonomic regulation, and their temporal dynamics are deeply intertwined, yet strongly modulated by cultural background and task characteristics. These results support a multidimensional view of engagement, in which cognitive efficiency, emotional activation, and physiological regulation interact rather than operate independently. Engagement emerges as a coordinated process involving central nervous system dynamics, autonomic adjustments, and affective responses, whose relative contribution depends on the nature of the task. Fast-paced, time-pressured games emphasize reactive control and rapid emotional transitions, while memory-based tasks rely more heavily on stable autonomic regulation and sustained cognitive focus. This task dependence underscores the importance of carefully selecting and designing game paradigms in experimental research, as different games probe distinct facets of cognitive and emotional processing. Another key outcome of this chapter is the demonstration that temporal dynamics carry critical information beyond static measures. Across modalities, performance and engagement were more consistently associated with changes over time, transition patterns, and stability of physiological signals than with absolute levels alone. This was evident in neural adaptation across gameplay phases, in pupillary latency and variability and in the structured evolution of FE trajectories and heart rate variability. These findings reinforce the notion that engagement is best characterized as a dynamic regulatory process rather than a fixed state, and that time-resolved analyses are essential for capturing its complexity. The inclusion of a cross-cultural perspective further strengthens the chapter's contribution by highlighting that engagement-related signals are not universally expressed in the same way. Cultural norms influence not

only the intensity of emotional expressions but also their timing, variability, and regulation during interactive tasks. This has important implications for both experimental design and the development of computational models, suggesting that engagement metrics derived from physiological and affective data should be interpreted within their cultural context to ensure generalizability and validity. From a methodological standpoint, the chapter demonstrates the added value of a multimodal approach. While single modalities provide partial insights, their integration allows for a more comprehensive characterization of engagement, revealing convergent patterns across neural, autonomic, and affective systems. At the same time, the interpretation of these multimodal markers requires careful consideration of the analytical procedures used to derive them. Several of the spectral EEG indices, pupilometric measures, and autonomic features considered in this chapter may be influenced by preprocessing strategies and parameter settings; consistent signal processing procedures (see subsection 2.3.1, subsection 2.4.2 and section 2.6) were therefore adopted across experiments to limit methodological variability and support the robustness of the extracted engagement markers. In addition, the analysis of FE dynamics during gameplay relied on a MC-inspired approach. While this framework provides a flexible way to capture temporal transitions in affective states, its outcomes may also depend on specific preprocessing and feature extraction choices. Given the relatively exploratory nature of this method in the context of game-based psychophysiology, further methodological work will be required to refine the processing pipeline and identify optimal parameter settings capable of improving the stability and reliability of the resulting FE dynamics estimates. This multimodal framework strengthens the interpretation of experimental findings and, more importantly, lays the groundwork for future adaptive and personalized applications, such as serious games for cognitive assessment, training, or rehabilitation, where real-time monitoring of engagement is essential. In conclusion, this chapter establishes game-based experimental paradigms as tools for studying cognitive and emotional processes in action. By showing how engagement manifests through coordinated and dynamic psychophysiological responses, the chapter bridges controlled experimental research and more ecologically valid interactive scenarios. It also provides a conceptual and methodological foundation for the next one, which further explores how cognitive and emotional processes are shaped by increasing levels of complexity, social interaction, and contextual modulation.

Chapter 5

Integrated Affective Neuroscience Across Individual and Dyadic Contexts: From Neuroaesthetic Processing to Interpersonal Synchrony

This chapter examines psychophysiological dynamics in affective and social contexts through three complementary experimental studies. The first investigates how individual traits modulate neural connectivity during aesthetic experience, highlighting distinct temporal contributions of expertise and empathy. The second explores autonomic responses in dyads exposed to shared emotional stimuli, showing how affective co-presence shapes electrodermal dynamics alongside individual variability. The third study addresses interpersonal neural coupling using EEG hyperscanning with cross-biofeedback, demonstrating that inter-brain synchronisation (IBS) reflects genuine relational processes and is modulated by emotional content and psychological characteristics. These studies provide a multilevel perspective on affective processing, spanning individual, shared, and interactive psy-

*chophysiological organization.*¹

Building on the experimental evidence presented in the previous chapters, this chapter addresses psychophysiological responses in contexts characterized by increased affective salience, social presence, and interpersonal interaction. While chapter 3 and chapter 4 progressively examined neural and autonomic dynamics under controlled perceptual stimulation and cognitively structured tasks, the focus here shifts toward scenarios in which emotional meaning and relational factors play a central role. This transition represents the final step in the simple-to-complex progression guiding the thesis, where internal states are no longer elicited solely by stimulus properties or task demands, but emerge from the interaction between individuals, stimuli, and social context. The three studies included in this chapter share a common objective: to investigate how affective content and social coupling modulate psychophysiological organization beyond the individual level. Rather than treating emotion as an isolated response to external stimuli, these paradigms explicitly consider emotional processing as embedded within relational and interactive frameworks. Across different experimental configurations, the chapter explores how neural and autonomic dynamics adapt when individuals are exposed to emotionally meaningful material, observe or share experiences with others, or engage in reciprocal interactions mediated by physiological feedback. In this sense, the studies collectively extend the multimodal perspective of the thesis toward contexts where individual and interpersonal processes are intrinsically intertwined. From a methodological standpoint, this chapter further develops the use of dynamic and connectivity-based analyses introduced earlier, applying them to emotionally and socially enriched environments. Functional connectivity metrics, autonomic indices, and hyperscanning approaches are employed to capture both intra-individual modulation and inter-individual coupling. Importantly, these analyses are not limited to descriptive characterizations but are used to probe how individual traits, shared affective experiences, and interactive feedback mechanisms influence the temporal organization of neural and autonomic responses.

¹The section 5.2 of this chapter has been published as “Quantitative Electrodermal Activity Analysis of Simultaneous Recordings from Dyads during Affective Visual Task: Proof of Concept and Preliminary Results” in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, vol. 2025, pp. 1–6, 2025 [423].

5.1 Temporal Dynamics of Functional Connectivity during Neuroaesthetic Experience: Effects of Art Expertise and Psychological Traits

5.1.1 Introduction

Neuroaesthetics, first formalized by Semir Zeki at the end of the twentieth century, has emerged as a rapidly expanding interdisciplinary field dedicated to elucidating the neural and cognitive mechanisms underlying the perception of beauty and the aesthetic appreciation of art [254,466,467]. Integrating methodologies from neuroscience, psychology, and art theory, neuroaesthetics addresses longstanding questions regarding the emotional impact of art, the neural substrates of aesthetic experience, and the influence of individual differences such as expertise and personality traits on responses to artworks. Recent advances in brain imaging and electrophysiological methods, such as functional Magnetic Resonance Imaging (fMRI) and EEG, have enabled the real-time examination of aesthetic experience, revealing that aesthetic judgment is not merely a subjective preference but is supported by specific neural networks. For example, the medial orbitofrontal cortex has been consistently associated with the evaluation of beauty and with reward-related processes, suggesting that the appreciation of art is deeply linked to mechanisms of pleasure and motivation [224]. Such findings underscore that aesthetic experience engages core systems of human emotion and cognition, highlighting art as a privileged window into the brain's dynamics. Embodied processes also mediate affective responses to art. Early studies on mirror neurons [362] have been pivotal in explaining how individuals can resonate with the emotions and intentions conveyed by artistic stimuli. Building on this, Freedberg and Gallese [156] demonstrated that even the mere observation of cuts in Lucio Fontana's canvases can activate motor systems in viewers, pointing to an embodied simulation mechanism that links perception, action, and emotion. Individual traits, particularly empathy, further modulate the intensity and quality of aesthetic experience. The IRI [115] has been widely used to assess dispositional empathy across different populations. Recent neurophysiological studies suggest that individual differences in empathy, as measured by the IRI, are reflected in oscillatory brain dynamics and prefrontal activations during interpersonal or affective tasks, often in conjunction with autonomic

responses [11, 28]. These findings indicate that empathy is not only relevant in social interactions but may also contribute to shaping aesthetic judgments and their underlying neural dynamics. In addition to empathy, expertise constitutes another determinant of how individuals perceive and evaluate art. Experts and non-experts employ distinct perceptual and cognitive strategies when engaging with artworks: experts rely more heavily on top-down interpretative schemes and contextual knowledge [342]. In contrast, non-experts tend to process visual features more directly. These differences are reflected both behaviorally and neurally, with experts showing distinct activation patterns [394]. Expertise, therefore, not only enriches interpretative depth but also influences the temporal unfolding of neural responses during aesthetic perception. Beyond theoretical implications, neuroaesthetics also opens perspectives for applied domains, such as education, museology, and therapy. Integrating insights from neuroscience into art education and museum practices has been proposed as a means to enhance emotional engagement, stimulate creativity, and strengthen learning processes [41, 284]. In this context, art emerges as a pedagogical tool capable of promoting both cognitive growth and emotional development, with potential applications that extend from classrooms to therapeutic contexts.

Against this background, the present study investigates how functional connectivity, measured using the PLI applied to EEG recordings, differs between art experts and non-experts, and how dispositional empathy modulates these dynamics. PLI has been widely used as a robust measure of functional connectivity because it minimizes the influence of volume conduction and common sources, making it particularly suitable for exploring the temporal coordination of neural oscillations during cognitive and affective tasks [188, 400]. Applying PLI to aesthetic experience enables the characterization of neural dynamics underlying art perception [408]. By combining EEG connectivity with behavioral and psychometric measures, this study investigates how artistic expertise and dispositional empathy shape the temporal unfolding of aesthetic processing. Specifically, it examines how these individual traits modulate functional connectivity when viewers engage with artworks that vary in their affective qualities, measured through valence and arousal.

5.1.2 Materials and Methods

Materials A total of 35 (16 F, 19 M; mean age, 22.86 ± 1.96 years) out of the 53 healthy participants who were involved in the experiment were analysed. This study was approved by the Institutional Review Board (endorsement of compliance with the Opinion of the Ethics Committee for Research no. 275 of 04/09/2023), and all participants gave their written informed consent. All subjects had normal or corrected-to-normal vision and reported no history of neurological or psychiatric disorders. Participants were divided into two main groups based on their level of art expertise, by recruiting students from the Accademia delle Belle Arti di Firenze (<https://www.accademia.firenze.it/>) and Engineering Students from the University of Florence. The experimental paradigm consisted of three phases, as shown in Figure 5.1.

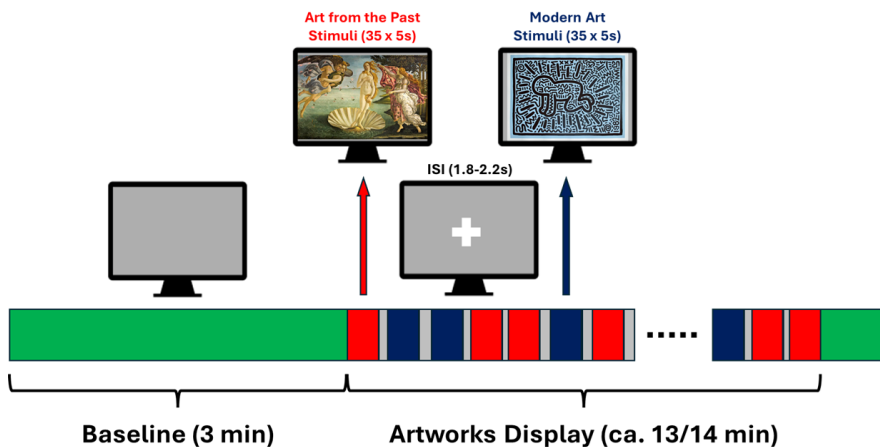


Figure 5.1: Framework and timeline of the proposed experiment. ISI = Inter-Stimulus Interval.

First, participants completed a 3-minute resting-state baseline with eyes open while fixating on a central cross. Then, they were exposed (~ 13 -14 minutes) to a randomized sequence of 70 visual stimuli in the form of paintings. The stimulus set included 35 artworks from the past and 35 from the modern period, selected by a panel of experts from the Accademia di Belle Arti di Firenze. Importantly, these experts did not take part in the EEG

recordings to avoid introducing bias. The selection was designed to represent a brain's spectrum of stylistic and emotional features, while ensuring balance across the two categories. Stimuli were presented on a computer monitor at a distance of approximately 70 cm from the participant's head. Each picture was displayed for 5 seconds, followed by a fixation cross for a variable inter-stimulus interval (1.8–2.2 s). The presentation order of artworks was random for each participant to account and partially mitigate the effects of fatigue in the subject pool across all stimuli. Also, participants were informed in advance about the specific set of artworks ('art from the past', 'modern art') that would be used in the experiment. The task concluded with a 10-second eyes-open baseline. During the task, EEG activity ($f_s = 300\text{Hz}$) was recorded using the dry-electrode DSI-24 wearable EEG headset (Wearable Sensing, San Diego, CA, USA). Participants sat comfortably in a chair in a dimly lit room and were instructed to remain still during stimulus presentation. A custom MATLAB script was developed to administer the experimental procedure, embedding event markers at each transition between phases and at the onset of each artwork. Following the EEG session, participants completed the SAM questionnaire [54] for each stimulus (see section 2.9), rating both valence and arousal on a 5-point Likert scale ranging from -2 (very negative/low arousal) to $+2$ (very positive/high arousal). Additionally, participants were asked whether they had previously seen each artwork (with a binary yes/no response). Figure 5.2 summarizes the overall evaluation of the proposed artworks in the arousal-valence space by participants, who also completed the Italian version of the IRI [9] to assess empathic predisposition (see section 2.9).

Methods EEG data were preprocessed in MATLAB with EEGLAB [120] following the HAPPE workflow [164], as previously described in subsection 2.3.1 (band-pass filtering 1–80 Hz). After preprocessing, the continuous EEG data were segmented into two epochs for each presented artwork: 0–1 seconds, aligned with stimulus onset, and 1–2 seconds post-stimulus onset, allowing for analyses of both early and late time windows of aesthetic processing. The PLI connectivity analysis was performed on these short, consecutive windows rather than on the entire 5-s stimulus period [91,243]. The 0–1 s window considers early, stimulus-driven connectivity dynamics associated with rapid perceptual encoding and initial affective appraisal, whereas the 1–2 s window reflects subsequent integration and evaluative processing, be-

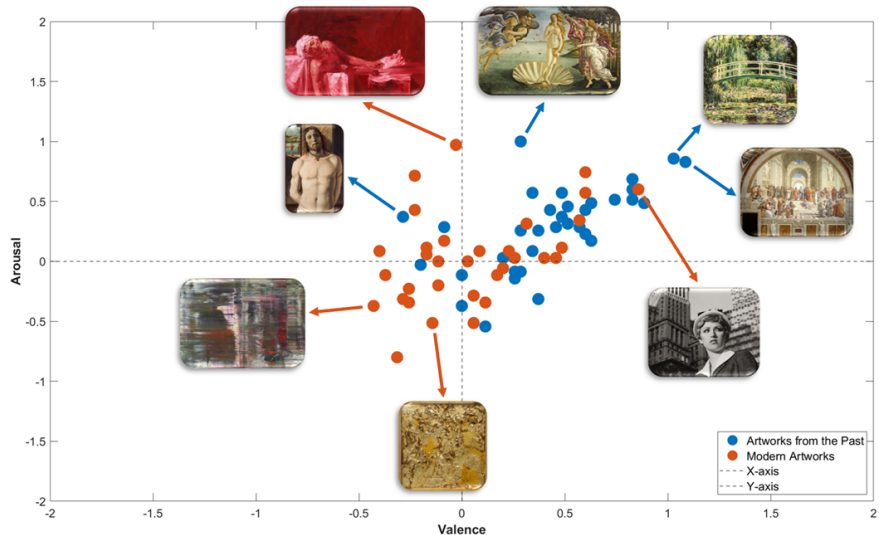


Figure 5.2: Distribution of artworks in the two-dimensional valence-arousal space based on participants’ ratings.

fore later time points where attentional drift, blinks, and motor adjustments typically increase. Longer windows (e.g., 0–5 s) risk conflating these distinct neural states and artificially inflating connectivity values due to averaging across heterogeneous activity [38].

Functional connectivity was quantified using the Phase Lag Index (PLI), as previously described in subsection 2.3.4. Specifically, PLI was computed using a modified version of the FCLAB toolbox for EEGLAB (available at: <https://github.com/FCLAB-UPV/>) [348]. Connectivity matrices were calculated separately for four canonical frequency bands of interest for EEG signals: theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–80 Hz). Each adjacency matrix obtained from the PLI computation was subjected to proportional thresholding, retaining only the top 20% of the strongest weights. Then, the graph-theoretical features described in in subsection 2.3.4 were calculated using the BCT [366] (see Equation 2.17–Equation 2.30). For each subject and condition, the median value of each metric across stimuli was calculated to reduce the influence of outliers and provide a more robust estimate of central tendency.

Statistical Analysis Statistical analyses were conducted to compare the extracted network features across groups and experimental conditions. Behavioral and EEG measures were integrated to examine how art expertise and empathic disposition modulated both subjective aesthetic judgments (valence/arousal ratings, familiarity) and neural connectivity dynamics. For expertise, experts and non-experts were compared globally across all artworks, testing both the median and the iqr of connectivity metrics, and separately on the 10 most known ($\geq 80\%$) and 10 least known ($\leq 22.86\%$) artworks across all participants, where only median values were considered. For empathy, comparisons were made between empathic and non-empathic participants globally on all artworks (testing both median and iqr), as well as on the 10 stimuli rated with the highest (≥ 0.629) and lowest (≤ -0.229) valence and the 10 rated with the highest (≥ 0.571) and lowest arousal (≤ -0.314), where only the median was analysed. Group differences in graph-theoretical measures derived from PLI were first tested for normality of distribution with the Shapiro-Wilk test (threshold $\alpha = 0.05$); since the assumption was not met, comparisons were carried out using the non-parametric Mann-Whitney U test.

5.1.3 Results

SAM & IRI Evaluation Table 5.1 reports the mean and standard deviation of valence, arousal ratings, and % of artworks known across all subjects, split between artworks from the past and modern artworks. Differences between these two categories were assessed using the Mann-Whitney U test, with an alpha threshold of 0.05. Results indicated significantly higher valence ratings for artworks from the past compared to modern artworks ($p < 0.001$), as well as higher arousal ratings ($p < 0.05$). No significant differences were observed in the percentage of artworks known. Table 5.2 further summarizes the same ratings split by expertise level, comparing experts and non-experts. In this case, group differences were tested using the Wilcoxon signed-rank test, with the same alpha threshold of 0.05. Experts reported significantly higher valence ratings ($p < 0.001$) and a larger proportion of artworks recognized ($p < 0.001$), while no significant differences emerged in arousal ratings. Moreover, participants were divided into two groups based on IRI scores: high-empathy (17 participants with total IRI score > 94 , corresponding to the sample median) and low-empathy (18 participants with total IRI score ≤ 94). This grouping enabled comparisons between individuals with varying

overall levels of dispositional empathy. Notably, experts showed higher IRI scores compared to non-experts (102 vs. 90.5, $p < 0.05$).

Table 5.1: Mean and standard deviation of valence, arousal ratings and % of artworks known for all proposed artworks. NS = Not Significant.

	Artworks from the Past	Modern Artworks	p-value
Valence	0.426 ± 0.327	0.072 ± 0.338	$p < .001$
Arousal	0.278 ± 0.351	0.053 ± 0.393	$p < .05$
% of Artworks known	$57.4\% \pm 26.5\%$	$48.6\% \pm 23.6\%$	NS

Table 5.2: Mean and standard deviation of valence, arousal ratings and % of artworks known comparing experts and non-experts. NS = Not Significant.

	Experts (n=17)	Non-experts (n=18)	p-value
Valence	0.408 ± 0.411	0.098 ± 0.49	$p < .001$
Arousal	0.226 ± 0.432	0.109 ± 0.462	NS
% of Artworks known	$70.8\% \pm 25.9\%$	$36.2\% \pm 27.8\%$	$p < .001$

Functional Connectivity Results To investigate the temporal dynamics of functional connectivity during aesthetic processing, analyses were performed for two consecutive windows: the initial epoch following stimulus onset (0–1 s) and the subsequent epoch (1–2 s). Significant differences emerged between groups defined by expertise and empathy, with frequency- and condition-specific patterns. Statistical significance was assessed using the non-parametric Mann-Whitney U test (threshold $\alpha = 0.05$). Values are reported as medians (Group 1 vs. Group 2).

In the first second after stimulus onset, expertise-related effects appeared in the theta and alpha bands. Across all artworks, experts exhibited lower transitivity in the theta band (0.145 vs. 0.160, $p < 0.05$, Figure 5.3) and higher participation in the alpha band (0.330 vs. 0.318, $p < 0.05$). The iqr analyses further revealed reduced betweenness centrality in experts in the theta band (4.112 vs. 4.644, $p < 0.05$, Figure 5.3). When focusing on the 10 most familiar artworks, the effect on theta transitivity was confirmed (0.145 vs. 0.155, $p < 0.05$). No significant differences emerged for the least familiar artworks. In contrast, global comparisons across all artworks did

not reveal statistically significant median differences between empathic and non-empathic participants. However, the iqr analyses revealed higher eigenvector centrality in the theta band for highly empathic individuals (0.020 vs. 0.014, $p < 0.05$). Stimulus-specific effects emerged: for high-valence artworks, empathic participants showed higher theta participation (0.332 vs. 0.307, $p < 0.05$); for low-valence artworks, lower alpha clustering (0.124 vs. 0.150, $p < 0.05$). High-arousal artworks elicited reduced gamma eigenvector centrality in empathic individuals (0.193 vs. 0.198, $p < 0.05$). Low-arousal artworks were associated with lower modularity Q in the alpha band (0.268 vs. 0.288, $p < 0.05$). No significant differences emerged in the comparison between artworks from the past and modern artworks.

In the second epoch, expertise-related differences shifted toward the beta and gamma bands. The iqr analyses across all artworks revealed that experts showed reduced beta betweenness (3.697 vs. 4.198, $p < 0.05$) and lower gamma participation (0.080 vs. 0.097, $p < 0.05$). For the 10 most familiar artworks, experts exhibited lower theta efficiency (0.320 vs. 0.336, $p < 0.05$), higher theta modularity Q (0.295 vs. 0.271, $p < 0.01$), and lower beta strength (1.106 vs. 1.141, $p < 0.05$). For the least familiar artworks, higher modularity Q was observed in the beta band for experts (0.295 vs. 0.280, $p < 0.05$). Regarding empathy-related comparisons, global analyses across all artworks revealed no significant effects during this epoch. However, differences emerged when considering stimulus valence and arousal. For high-valence artworks, empathic participants showed longer characteristic path length in the alpha band (4.194 vs. 3.768, $p < 0.05$), reduced efficiency (0.297 vs. 0.330, $p < 0.05$), higher modularity Q (0.295 vs. 0.263, $p < 0.01$), and increased betweenness centrality (19.889 vs. 18.480, $p < 0.05$) (Figure 5.4). In the gamma band, they also exhibited higher transitivity (0.058 vs. 0.047, $p < 0.05$) and clustering (0.051 vs. 0.044, $p < 0.05$). For low-valence artworks, empathic individuals displayed higher theta transitivity (0.164 vs. 0.138, $p < 0.05$) but lower participation (0.310 vs. 0.333, $p < 0.01$). High-arousal artworks elicited higher eigenvector centrality in both beta (0.197 vs. 0.194, $p < 0.05$) and gamma bands (0.194 vs. 0.199, $p < 0.05$). No significant differences emerged for low-arousal artworks. Finally, artworks from the past yielded higher clustering values in both beta (0.075 vs. 0.074, $p < 0.01$) and gamma bands (0.047 vs. 0.045, $p < 0.05$).

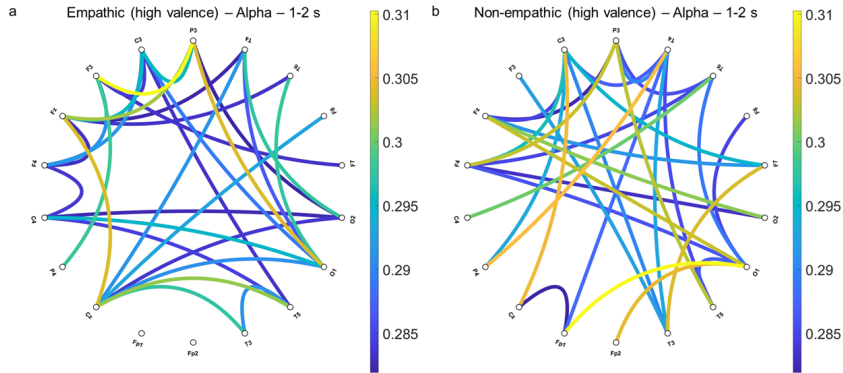


Figure 5.4: Functional connectivity graphs in the alpha band (1–2 s) for (a) empathic and (b) non-empathic across the 10 artworks rated with highest valence. Edges represent the strongest 20% of PLI connections, with color reflecting connection strength.

5.1.4 Discussion

The present study investigated how art expertise and dispositional empathy modulate large-scale neural connectivity during the perception of artworks, focusing on early (0–1 s) and slightly later (1–2 s) post-stimulus epochs. By applying the PLI to EEG recordings and deriving graph-theoretical measures, temporal and frequency-specific patterns associated with individual traits were identified. Although exploratory in nature, these findings offer preliminary yet meaningful insights into the temporal unfolding of neural dynamics during aesthetic experiences. Results (Table 5.3) show that art expertise produces specific functional dynamics during the initial second of visual processing, particularly in the theta and alpha bands. Across all artworks, experts exhibited reduced transitivity (median) and betweenness centrality (iqr) in theta (Figure 5.3), along with higher participation in alpha, suggesting that expertise facilitates a more efficient redistribution of information and reduces redundant local clustering at early stages of aesthetic perception. These effects were confirmed when considering the most familiar artworks, highlighting the role of recognition and prior knowledge in modulating early connectivity. By contrast, no differences emerged for

the least familiar artworks, suggesting that expertise-related advantages are most pronounced when prior representations can be recruited. In the subsequent 1–2 s window, expertise effects became more selective: experts showed reduced betweenness (beta) and participation (gamma) across all artworks, and for familiar artworks, lower efficiency and strength but higher modularity in theta and beta bands. This pattern indicates a shift from global integration to more modular and specialized processing, consistent with evidence that aesthetic experience involves dynamic reconfiguration of connectivity over time [269]. Together, these results align with previous findings showing that art expertise modulates perceptual and attentional mechanisms during early processing [141] and that connectivity differences emerge depending on familiarity and stylistic recognition [408]. Empathy, in contrast, showed a different temporal profile (Table 5.3). In the first second, empathy effects were limited: across all artworks, empathic individuals only exhibited higher eigenvector centrality in theta, suggesting subtle increases in the relative influence of certain nodes. Stimulus-driven differences emerged more clearly, with higher participation in theta for high-valence artworks, reduced clustering in alpha for low-valence artworks, and differential modulation of eigenvector centrality in gamma and modularity in alpha depending on arousal. These findings suggest that, unlike expertise, empathy did not globally alter connectivity during initial perceptual encoding but instead interacted with affective properties of the artworks. In the 1–2 s epoch, empathy effects became more widespread. For high-valence artworks (Figure 5.4), empathic participants exhibited longer path length, reduced efficiency, and increased modularity and betweenness in the alpha band, suggesting a less integrated but more segregated network configuration. They also showed additional modulations in gamma-band transitivity and clustering, pointing to valence-specific reorganization of large-scale dynamics. For low-valence artworks, differences in theta transitivity and participation suggested altered segregation and integration processes. High-arousal artworks elicited changes in centrality metrics across beta and gamma, reflecting their emotional salience, whereas no significant differences emerged for low-arousal artworks. This temporal profile suggests that empathy primarily influences the evaluative and affective appraisal phase of aesthetic processing, consistent with theoretical accounts linking empathy to affective resonance and social-emotional engagement during aesthetic experience [59]. These findings highlight complementary roles for expertise and empathy in shaping

the neural dynamics of aesthetic perception. Expertise exerts its main effects during early perceptual stages and in relation to familiarity, facilitating efficient information flow and network specialization. Empathy, by contrast, shows weaker global effects at stimulus onset but stronger and more stimulus-dependent modulations in later evaluative stages, especially as a function of valence and arousal. This dual temporal signature underscores how cognitive and affective traits differentially shape aesthetic experience: expertise enhances recognition- and knowledge-based processing, while empathy modulates affective resonance and evaluative integration. Importantly, the heterogeneity of responses observed across conditions supports the idea that aesthetic experience is not determined solely by the properties of artworks but is shaped by individual traits. This interpretation resonates with recent EEG evidence showing that inter-individual cognitive and emotional differences significantly shape neural responses to visual stimuli over time [424]. From this perspective, it can hypothesize that neuroaesthetic interventions aimed at enhancing cognitive or emotional engagement should be tailored to individual dispositions to be effective, rather than adopting a one-size-fits-all approach. Personalized strategies could thus maximize the potential of art-based interventions in educational or therapeutic contexts. Several limitations of the present study should also be acknowledged. First, the small sample size limits the generalizability and statistical robustness of the findings. Although the observed effects are consistent with prior works in neuroaesthetics [59, 141, 269], the limited participants' pool inevitably constrains statistical power and increases susceptibility to small-sample variability. Future studies should therefore include larger and more heterogeneous populations to enhance reproducibility. Moreover, artworks were presented as digital images in a controlled laboratory setting; future research should examine whether similar effects emerge in more immersive contexts, such as virtual reality (VR) interventions or real-world environments including museums and galleries. Second, the stimulus set was restricted to paintings, which limits generalization to other artistic modalities. The number of stimuli represented a compromise between ecological variety and participant comfort, yet future work should consider expanding the stimulus space to incorporate additional categories and sensory domains. Third, although the DSI-24 system enabled rapid, wireless EEG acquisition, its relatively low spatial resolution constrains the precision of connectivity analyses and the interpretability of network-level findings. Higher-density EEG systems would

allow a more fine-grained characterization of neural dynamics. While a comparative analyses across different connectivity metrics could strengthen these findings, such comparisons were beyond the scope of the present study. The aim was primarily to develop an integrative framework capable of examining how individual characteristics, such as expertise and empathy, modulate neural and subjective responses over time. Future work should articulate this theoretical contribution more explicitly and further validate the stability of network patterns across connectivity metrics. Finally, future research could benefit from combining EEG with eye-tracking measures, as gaze behavior systematically varies with the emotional and aesthetic properties of visual stimuli, providing complementary insights into attentional allocation and appraisal processes [249].

5.2 Quantitative Electrodermal Activity Analysis of Simultaneous Recordings from Dyads during Affective Visual Task

5.2.1 Introduction

Recently, a growing interest has been in characterizing emotional and affective states in subjects by combining psychological and physiological quantitative analysis. Numerous studies have explored the dynamics of the CNS and ANS through the examination of various biosignals, including EEG [71], HRV [6, 71] and EDA [174, 203, 248]. Additionally, neuroimaging techniques such as functional Near-Infrared Spectroscopy (fNIRS) and fMRI have been utilized [406]. These studies suggest a potential link between the physiological and psychological domains in understanding human emotions and affective states. Moreover, further studies provided novel methods to analyze interactions between multiple subjects from a neurophysiological and psychological point of view [314, 328]. In this context, the so-called hyperscanning method was proposed as a novel tool aiming at investigating the biological processes that may exist or are established in two or more subjects when they are socially interacting or participating in the same cooperation task, emotional experience, or learning paradigm [470]. For the characterization of dynamics between subjects, most of these studies used mainly EEG systems simultaneously applied to two or more participants [189, 465]. Furthermore,

other physiological signals have been explored as complementary or supplementary sources of information to EEG in hyperscanning studies [71]. However, few works still explore using different signals in a hyperscanning context. For instance, the EDA signal has been extensively studied for its role in characterizing emotional and physiological states [175,305], detecting mood disorders [14,247,374], and assessing its variations during cognitive or affective stimuli in individual subjects [45,452]. This supports the idea that EDA analysis can capture certain ANS dynamics related to emotional processing [203]. Furthermore, while relatively few studies have explored the use of EDA in hyperscanning paradigms [6,437,462], existing findings suggest that EDA can be considered either independently or in conjunction with other physiological signals. In this work, a novel EDA-based system was preliminarily designed and validated on a first cohort of healthy subjects. EDA signals were recorded simultaneously on two subjects during an affective visual task. The study aimed to investigate EDA signals as indirect measurements of ANS dynamic response to the affective stimulation, evaluating if EDA might catch such dynamics.

5.2.2 Material and Methods

Experimental Setup In this work, 32 out of the total 37 healthy volunteers who took part in the experimental task were analysed, composing 16 dyads (18 F and 14 M aged between 19 and 28 (22.1 ± 1.6 y.o.)). Only two out of the 32 subjects were left-handed. This study was approved by the Institutional Review Board (endorsement of compliance with the Opinion of the Ethics Committee for Research no. 275 of 04/09/2023), and all participants gave their written informed consent. Each dyad sat on chairs in front of the same monitor where visual stimuli were presented. For the simultaneous acquisition of EDA signals from the two subjects, a dedicated firmware was implemented into a customized microcontroller platform based on an Arduino MKR WIFI 1010 [18].

Two identical EDA front-end sensor interfaces [407] were applied to each subject composing the dyad, with the electrodes positioned on the medial phalanges of the index and middle fingers of the non-dominant hand: each sensor was connected to the microcontroller unit with their dedicated pin and to a breadboard to connect both of them to the Arduino's ground and power supply pins. The sampling frequency of each acquired EDA was set to 50 Hz, and a moving average filter was applied to each acquired raw signal. The

experimental setup, stimulus timing, signal streaming, image presentation, and analysis of the collected EDA signals were performed using MATLAB. In addition, a trigger signal was added to monitor the experiment’s status and compute the corresponding EDA features for each stimulus. A subset of 104 images from the International Affective Picture System (IAPS) [250] was selected as visual affective stimuli. According to Greco et al., [176], these images were selected and administered in terms of their level of arousal reported in [250]. As shown in Figure 5.5, a baseline period of 3 minutes’ rest, in which dyads were asked to relax, preceded the visualization of images. The sequence of the images was defined as follows: four active sessions (AS) of 20 stimuli each (from T1 to T4 in Figure 5.5), ordered in terms of increasing arousal to minimize emotional carryover effects and allow clearer interpretation of EDA responses across arousal levels. Between each AS, four neutral sessions (NS in Figure 5.5) of 6 stimuli each were proposed to the subjects. These periods were intended to reset participants’ physiological or psychological state and were composed of images with the lowest level of arousal from the IAPS dataset. More details on each session’s arousal level are reported in Table 5.4. Each image was shown for 10 s, and the overall average duration of each recording was about 20 minutes.

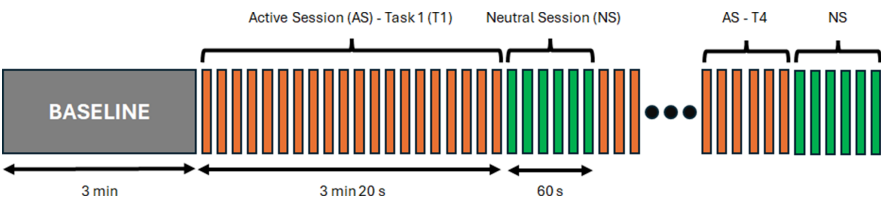


Figure 5.5: The framework of the proposed experiment with IAPS images.

Table 5.4: Arousal level from the IAPS database and the SAM test for each session administered to the subjects.

Session	IAPS Arousal Rating	SAM Arousal Rating (32 subjects)
N	2.81 ± 0.24	4.28 ± 1.80
T1	3.58 ± 01.30	4.99 ± 1.41
T2	4.60 ± 0.31	5.40 ± 1.40
T3	5.55 ± 0.28	6.38 ± 1.48
T4	6.50 ± 0.33	7.25 ± 1.41

Each AS and NS were composed of 20 and 6 images, respectively. In addition, for each dyad in each session, the order of presentation of the images was randomized. After the experiment, each participant compiled the SAM [54] test to evaluate arousal, valence, and dominance of all the presented images. Figure 5.6 shows the collected EDA signals of a dyad and its corresponding trigger signal.

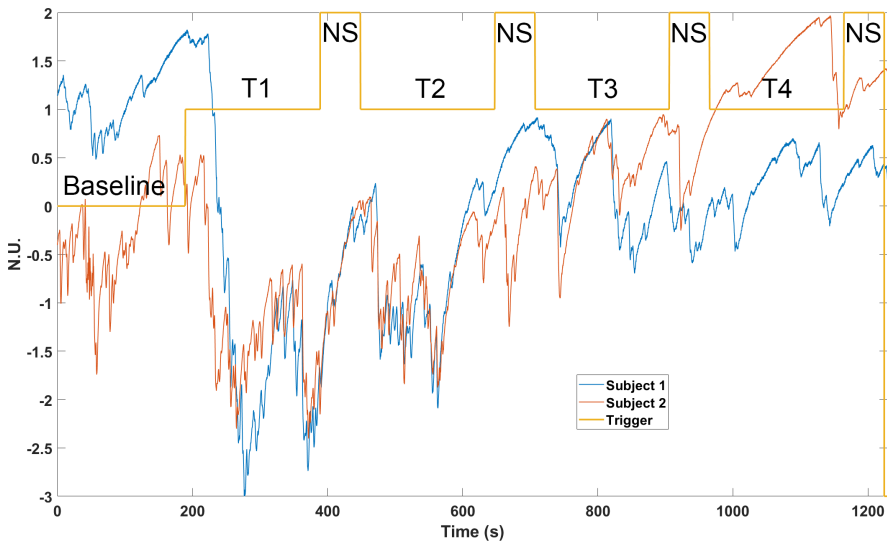


Figure 5.6: Example of two EDA signals collected simultaneously on two subjects. Blue and red lines represent the EDA signal for Subject 1 and Subject 2, respectively. The trigger, orange line, is reported in discrete values: 0 = Baseline, 1 = AS, 2 = NS. N.U. = normalized units.

EDA Analysis For EDA processing, the *cvxEDA* algorithm was used to obtain the cleaned SCL and SCR components, as previously described in subsection 2.4.2. Before applying it, EDA signals were low-pass filtered at 3 Hz with an FIR filter ($n = 300$) with a transition band spanning from 3 Hz to 5 Hz and normalized using a Z-score transformation to facilitate model convergence. Figure 5.7 shows the tonic and phasic signals for two raw EDA signals, already shown in Figure 5.6, after decomposition. According to Baldini et al [29], SCL- and SCR-related features reported in subsection 2.4.3 were evaluated for each stimulus presented to the subjects.

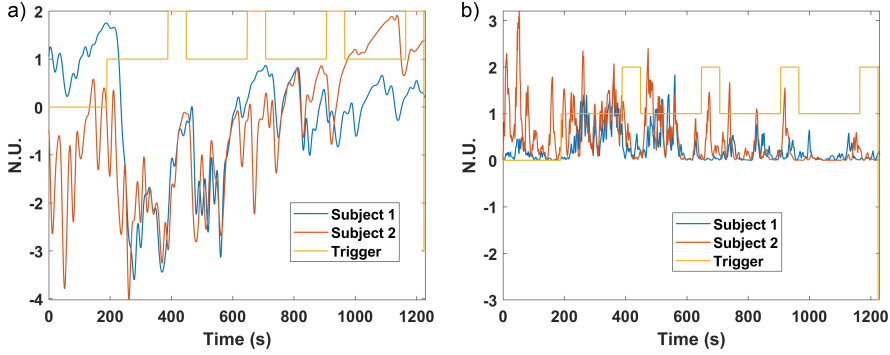


Figure 5.7: Decomposition for the signals shown in Figure 5.6. (a) Tonic component (b) Phasic component. Red and blue lines represent the decomposed signals for Subject 1 and Subject 2, respectively. The orange line is the trigger signal (in compact form). N.U. = normalized units.

Statistical Analysis This work evaluated two main hypotheses on EDA features: one without considering the simultaneous recording of the signals (intra-subject test) and the other to evaluate specific dynamics on the dyads (inter-subject test). Specifically, the first hypothesis was designed to assess whether EDA features may vary according to the AS administered and therefore if they are related to the level of arousal represented in the images (from T1 to T4). Specifically, this analysis was performed to verify if the selected visual stimuli could elicit significant dynamics on the EDA signals for all subjects. Statistical analysis was performed on all EDA features extracted from each stimulus. Before applying statistical tests, the distribution of each feature was evaluated by the Shapiro-Wilk test (significance level 0.05). Then, if the normality hypothesis was violated, the non-parametric Kruskal-Wallis test was adopted; otherwise, the ANOVA test (significance level 0.05) was used. Then, after the Tukey-Kramer post hoc correction, each pairwise comparison between each AS (e.g., T1 vs. T4) was evaluated to find which session showed the highest differences in terms of EDA features for all the subjects. The second statistical analysis considered the paired differences in EDA features when the same image was administered to each dyad. This analysis aims to evaluate if statistically significant differences might arise according to the different arousal levels of the image shown in the EDA dynamics on dyads. The analysis aimed to find possible discrepancies in EDA

dynamics when the same stimulus was administered to the two subjects. For this analysis, the paired t-test was considered for each AS separately (from T1 to T4, significance level 0.05). If the normal distribution hypothesis was violated, the Wilcoxon signed-rank test was used. All these analyses were performed for each EDA feature considered.

5.2.3 Results

In Table 5.5, the statistical results obtained on the intra-subject analysis are shown. Five dyads were excluded before the statistical analyses due to the high noise level on EDA raw signals. Thus, a total of 22 subjects were considered. For clarity, the EDA features obtained from the NS were not analyzed in this work. Twenty observations per subject for each AS were analyzed, obtaining 440 observations for a single EDA feature for each AS level. Moreover, the outliers across all the observations for each session were removed. In this work, an outlier was defined as a value on EDA features that is more than three scaled MAD from the median; this was done because MAD is robust to outliers and skewed distributions, which are common in EDA signals. This process was repeated for each feature reported in Section IIB. In Table 5.5, only the statically significant features after the post hoc correction are reported (significance level 0.05).

Table 5.5: Statistical analysis results on 22 subjects. Only the statistically significant EDA features are reported for each AS comparison. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$.

Task	vs. T2	vs. T3	vs. T4
T1	SCL (mean***, std***) NCSSR (ampsum**) EDA symp *** SCR (peak***, ampsum**)	SCL (mean***) NCSSR (ampsum**) EDA symp*** SCR (peak***, n**, ampsum***) Lat1**	NSSCR (n*, ampsum**) EDA symp*** SCR peak**
T2	-	SCL (std***)	SCL (mean***, std***) NSSCR (n**)
T3	Same for T2 vs. T3	-	SCL (mean***) NSSCR (n***) SCR (ampsum**)

It is noteworthy that most of the differences lie in the SCL mean parameter for the T1 task versus all the other AS and also between T2 and T3 than T4 (SCL mean: T1=0.08±0.68, T2=0.37±0.37, T3=0.38±0.34,

$T4=0.10\pm0.67$). Significant differences were also found on the SCL std feature mainly between T1 and other AS and between T2 and T3 (SCL std: $T1=0.02\pm0.02$, $T2=0.01\pm0.02$, $T3=0.03\pm0.04$, $T4=0.02\pm0.03$). Moreover, several differences were found in the NSSCR parameters (mainly NSSCR n and NSSCR ampsum) and SCR peak.

Table 5.6 reports the statistical results related to the inter-subject analysis across 11 dyads (after removing the dyads with corrupted EDA signal). As in Table 5.5, only statistically significant features for each AS are reported. Focusing on NSSCR features, it is noteworthy that significant differences arise in later AS, where the level of arousal increases. Differences were found both for NSSCR n ($T1=3.23\pm2.52$, $T2=3.33\pm2.55$, $T3=3.63\pm2.62$, $T4=2.71\pm1.45$) and for NSSCR ampsum ($T1=3.93\pm4.68$, $T2=25.96\pm7.65$, $T3=6.25\pm7.67$, $T4=6.12\pm7.88$). In other words, the differences in the EDA dynamics between each dyad tend to be statistically greater than 0 when the level of arousal increases according to the AS administered. A difference equal to 0 means that, on average, all the subjects exhibited the same EDA variations in the session. An illustrative example is in Figure 5.8 to better explain this concept. The kernel density estimates for the paired differences on the NSSCR n feature for each AS are shown. Moreover, the same behavior was observed for the parameter SCR peak ($T1=2.59\pm2.61$, $T2=3.76\pm3.79$, $T3=3.86\pm3.84$, $T4=3.55\pm3.68$).

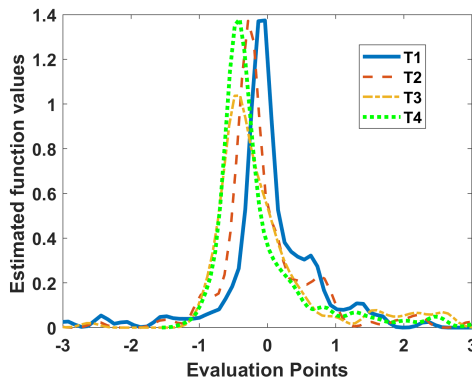


Figure 5.8: Probability Density Estimate for the parameter NSSCR n (paired differences) for each AS.

Table 5.6: Statistical analysis results on 11 dyads. Only the statistically significant EDA features are reported for each AS. *** $p<0.001$ ** $p<0.01$ * $p<0.05$.

AS	EDA Features
T1	SCL (mean*), EDA symp**
T2	SCL (mean*, std*), NSSCR (peak*, n*, mean***), EDA symp*, SCR (peak**), Lat 2*
T3	SCL (mean***, std**), NSSCR (n***), SCR (n***, ampsum*)
T4	SCL (mean***, std*), NSSCR (n***, mean**), SCR (peak*, n**)

5.2.4 Discussions

This work aims to evaluate differences in EDA signals on dyads acquired simultaneously during the same visual affective task. It provides a first proof-of-concept for designing EDA-based hyperscanning paradigms involving visual affective stimuli, highlighting the potential to capture subtle co-experienced physiological dynamics even without explicit interaction between individuals. As shown in Table 5.5, preliminary intra-subject analysis confirmed that the increasing level of arousal elicited different dynamics on EDA signals, as already reported in literature [378,439]. Significant differences were found between T1 and T4 since they represent the highest arousal content distance among sessions. On the contrary, T2 vs. T3 did not show differences in EDA features. It could be justified by the perception subjectivity of such stimuli for this cohort, which may differ from the original IAPS database evaluation (e.g., difference in cultural or age), as already documented in [57]. However, this preliminary analysis suggested that AS increasing levels is helpful in identifying statistically significant differences in EDA signals on multiple subjects. Moreover, as shown in Table 5.6, analysis on dyads suggested AS differences between each subject may vary according to the level of arousal, confirming that one subject may respond differently than the other subject in response to the same stimulus. Notably, some dyads reflected the same or common dynamics on EDA signal and related features. As shown in Figure 5.6, a correlation pattern between EDA dynamics during the experiment is present. This aspect opens several questions such as the level of participant dyad relationship, the perception of the affective stimulus, the level of empathy, the feeling of vulnerability that the participants could experience when exposed to affective stimuli, and other [171]. All these aspects should be considered in future developments to find possible links between the physiological and psychological domains. Moreover, focusing on

the global sympathetic activity (SCL mean) not all the differences found may be related to the proposed stimulation or at least not only, but they could just represented specific subjective conditions of each participant, regardless of the experiment. For example, the SCL mean was significantly different for each condition in Table 5.6 among dyads, and may be related to the other psychophysiological factors [434].

In comparison, differences found in NSSCR and SCR are more specific to the stimuli and how the participants reacted to them. As previously mentioned, this is the first preliminary study on EDA signals acquired simultaneously on two subjects during the same visual affective tasks. Even if the preliminary results are encouraging, some limitations are present, such as the low number of participants that limits the generalization and characterization of EDA dynamics for these stimuli. Moreover, in this work, only a paired analysis of dyads was conducted using classical EDA features. Future research should consider specific EDA features characterizing the dynamics between the dyads [26]. An interesting approach was presented by Sanchez [373], to evaluate common EDA dynamics on a single subject when different body sites were considered (e.g., on left and right hands). Furthermore, the integration of EDA features with other psychometric data, such as valence or dominance, may provide a more comprehensive understanding of emotional and physiological responses. For these reasons, specific statistical analysis will be performed in future developments, separating this cohort according to the SAM test collected after the experiments. In conclusion, this study highlighted possible methods and pipelines to characterize EDA dynamics on multiple subjects during affective visual tasks. Although the subjects did not interact directly or received biofeedback stimuli, this setup ensured shared environmental conditions and precise synchronization of stimuli, reducing potential confounds related to session variability. Moreover, it provides a more ecologically valid co-presence scenario and enables future analyses of passive inter-subject coupling or hyperscanning metrics. Future developments might also investigate the integration of intra- and inter-subject biofeedback mechanisms to enhance the hyperscanning paradigm, paving the way for novel EDA-based multi-subject measures.

5.3 Brain-to-brain Emotional Interaction Dynamics under Cross-Biofeedback EEG Hyperscanning

5.3.1 Introduction

Social interaction constitutes a fundamental component of human experience, exerting a profound influence on both cognitive and emotional processes [101]. In recent years, advances in neuroscientific methods have enabled the investigation of the neural mechanisms underlying interpersonal interactions. Traditional neuroimaging approaches, however, have primarily focused on the individual brain in isolation, providing important insights but failing to fully capture the inherently dynamic and reciprocal nature of social behaviour. Indeed, social cognition does not emerge solely from the activity of a single brain, but from continuous exchanges between individuals, where verbal and nonverbal cues (such as gestures, facial expressions, and postures) shape mutual understanding [190]. As highlighted by Hari and Kujala [190], a comprehensive account of the neural basis of social cognition requires moving beyond the paradigm of single-person neuroscience to that of two-person neuroscience, embracing a framework that allows the simultaneous investigation of interacting individuals.

To address this gap, Hyperscanning (HS) has been introduced as a powerful technique for the simultaneous acquisition of neural signals from two or more participants engaged in a shared task. By enabling the study of brain-to-brain coupling, HS provides a unique methodological framework to explore how interpersonal dynamics manifest at the neural level. Specifically, it enables the examination of interpersonal neural synchronisation, particularly in terms of the phase alignment of neural processes between interacting participants. This neural synchronisation may facilitate social interaction by enhancing the ability to anticipate and adapt to each other's behaviour, thereby promoting mutual understanding and coordinated action [101] [417]. Capturing these dynamics advances the understanding of the neural mechanisms underlying social behaviour and empathy. It may support both clinical applications (e.g., assessment and treatment of disorders affecting social functioning) and technological developments, such as multi-user Brain-Computer Interfaces. Hyperscanning can be implemented using various neuroimaging modalities, including fNIRS, EEG, Magnetoencephalography (MEG), and

fMRI. Among these, EEG and fNIRS have proven particularly suitable for studying dynamic social interaction, due to their integration with wearable systems that allow participants to move freely [393]. Although early references to Hyperscanning-like approaches date back to the 1960s [130], the first detailed implementation of EEG-HS configuration was proposed by Babiloni et al. (2006) [24]. Since its introduction, the growing interest in Hyperscanning has generated an expanding and diverse body of literature, covering cooperation and competition tasks, music, gaming, and affective processing, as reviewed by Czeszumski et al. (2020) [101]. The analysis and interpretation of Hyperscanning data remain challenging due to the difficulty of distinguishing genuine inter-brain relationships from spurious correlations induced by shared task engagement among participants [101]. Common analytical approaches include measures of coupling and connectivity, correlation and dependence metrics, graph theory measures, and information flow analysis. A widely used parameter is the PLV, which quantifies the degree of phase synchronisation between two signals within a given time window [343] [464] [131].

Another widely applied method, particularly in fNIRS studies, is Wavelet Transform Coherence (WTC), which estimates the coherence between two neural signals across both time and frequency domains [99] [200] [419]. Beyond the measurement of interpersonal neural synchronisation (INS), Hyperscanning can also be combined with neurofeedback (NF). Neurofeedback enables participants to voluntarily modulate specific aspects of their brain activity, supported by online feedback obtained from neural parameters [291] [27]. Within this framework, hyper-neurofeedback (hereinafter hyper-NF) extends NF to the interpersonal domain, delivering shared feedback based on parameters calculated in real-time. Recent studies have shown that hyper-NF can not only measure but also actively modulate neural synchronisation between individuals [235]. Feedback may be delivered through different sensory modalities (e.g., visual or auditory) and can vary in terms of timing and complexity.

A central methodological challenge in Hyperscanning is determining whether observed inter-brain synchrony (IBS) truly reflects interactive social processes, or whether it merely arises from co-executed, stimulus-locked tasks [327]. Hyper-NF may provide a promising framework to explore causal relationships in inter-brain dynamics, supporting its integration into paradigms investigating social cognition and interaction [327].

The present study addresses all these issues by investigating inter-brain dynamics in a Hyperscanning paradigm where dyads were exposed to visual stimuli with varying emotional content. During a dedicated phase, participants also received online cross-biofeedback, where an index of individual emotional engagement was computed from each subject’s EEG and visually transmitted to both members of the dyad. The cross-biofeedback approach was hypothesised to be a potential method for probing the causal relationships between participants’ brain activity and the dynamics of social interaction.

5.3.2 Material and Methods

Participants Fifty healthy volunteers were recruited, comprising 25 dyadic pairs (34 F and 16 M), aged 18-26 years (mean age 20.8 ± 2.3 years). The study was approved by the Institutional Review Board (Ethics Committee Opinion No. 275, dated April 9, 2023), and all participants provided written informed consent. Participants were selected following a preliminary screening questionnaire that included exclusion criteria related to neurological conditions and visual impairments. The pairs were formed to achieve a balanced distribution of familiar and unfamiliar dyads. The term "familiar" refers to dyads in which the two individuals have known each other for at least three months. The term "unfamiliar" relates to individuals who have never met before or have known each other for less than 3 months.

The cohort was characterised psychometrically using a series of psychological assessments, including the QCAE [185], the TAS 20 [196], the SPS [196] and the SIAS [361], previously described in section 2.9. The median and iqr values of the subjects’ scores for the tests are shown in Table 5.7.

Table 5.7: Median and iqr values for the psychometric tests used.

	Median (iqr)
QCAE	80.00 (5.25)
Cognitive Empathy (CE)	28.00 (4.25)
Affective Empathy (AE)	28.00 (3.00)
TAS	60.00 (6.25)
SIAS	32.00 (8.25)
SPS	21.00 (13.25)

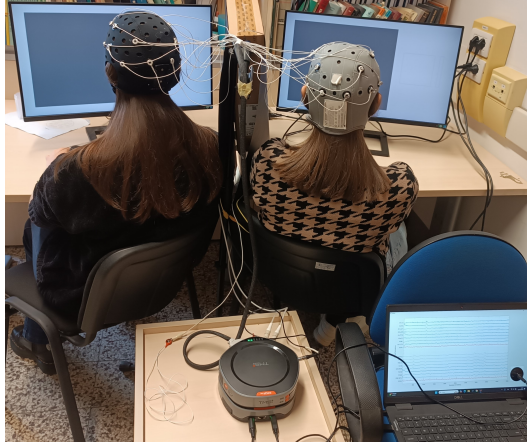


Figure 5.9: Preliminary experimental setup: each participant wears an EEG cuff with 16 electrodes connected to the SAGA amplifier. A separator system is placed between the two subjects. On the right is the Control Computer, which, through a photodiode placed on the bottom left corner of the screen, monitors the transition of the screen image.

Experimental Paradigm and Acquisition Setup The experimental setup required each dyad to be seated on chairs facing two identical monitors; a separator system was placed between the two subjects to prevent either participant from seeing the other's screen. The preliminary experimental setup is shown in Figure 5.9.

EEG signals from both participants were monitored using a single high-density amplifier (TMSi SAGA 32+/64+, TMSi, Oldenzaal, Netherlands) [430]), which was connected to a single EEG 32-electrode system. Electrodes were split between the two participants' cuffs (16 wet electrodes each), and each reference was managed with a Y-ground distributor, allowing both signals to be simultaneously displayed and recorded [129]. The following longitudinal unipolar montage was adopted throughout the entire experiment: Fp1, Fp2, F7, F8, F3, F4, C3, C4, T3, T4, T5, T6, P3, P4, O1, O2. These electrodes were split to cover each region of the scalp according to the 10/20 standard system, excluding the central electrodes due to the limited number of electrodes available. ECG signals were acquired from both participants using dedicated bipolar ExG channels of the TMSi SAGA amplifier. The sampling frequency for all signals was $f_s = 500Hz$; stimulus

timing, signal streaming, image presentation, and subsequent physiological signal processing were managed using MATLAB 2024a. A photodiode placed in the bottom-left corner of the screen was connected to the SAGA binary trigger to monitor the visual stimulus transition throughout all experimental phases. Moreover, a custom trigger signal was also implemented in MATLAB to track the experimental states.

A subset of 60 images was selected from the IAPS, considering their arousal and valence ratings [251]. In each stimulation phase of the protocol, images were distributed across four phases, as summarised in the Table 5.8. The first block included images with low arousal and low valence (LALV); the second block consisted of images with low arousal and high valence (LAHV); the third block featured images with high arousal and low valence (HALV); and the fourth and final block comprised images with high arousal and high valence (HAHV). Within each block, images were presented in a randomised order, with a different sequence used for each acquisition session. The experimental protocol consists of two visual stimulation phases, each separated by control phases (baseline). The procedure begins with a 2-minute baseline during which the interface (see Figure 5.10) is displayed to both participants and remains static. The first stimulation phase, hereinafter referred to as the "No Biofeedback (NOBF)" phase, involves the presentation of 40 static images, each displayed for 2 seconds and interleaved with a fixation cross, which is shown for a random time interval spanning 0.75–1.75 s.

A second 2-minute baseline follows. Then, a new stimulation phase, hereinafter referred to as the "Biofeedback (BF)" phase, is presented. This phase mirrors the structure of the previous stimulus phase but introduces the delivery of biofeedback stimuli, in both intra- and inter-brain modalities. It comprises 20 images, presented in alternation with a fixation cross. As in the previous phase, the images are divided into four blocks based on arousal and valence levels. Each image is displayed for 2 seconds, followed by a 3-second interval during which the EEG signal is processed in real time to extract the feedback metric. Unlike the previous stimulation phase (NOBF), this biofeedback implementation allows participants to perceive dynamic visual feedback reflecting their emotional states (see section 5.3.2). Cross-biofeedback was implemented via colour variation in specific components of the visual interface presented to participants, notably changes in the colour of a square and the background. The interface displayed both individual and cross-participant data, enabling participants to receive real-time

visual feedback that reflected their own emotional responses as well as those of their partner.

As shown in Figure 5.10, the *BF* column illustrates the sequence of sub-phases that occur after each image during the biofeedback phase:

- The appearance of a coloured square indicates the other participant's response to the image (other's feedback) (see Figure 5.10a).
- The appearance of background colour reflects the participant's response (individual feedback) (see Figure 5.10b).
- A subsequent modulation phase displays the change of both square and background colours, providing real-time feedback on mutual responses (see Figure 5.10c).

The third and final 2-minute baseline follows the second stimulation phase. The entire experimental session lasts approximately 16 minutes (mean value of 15 minutes 43 seconds $\pm$ 6.7 seconds), and a visual representation of the experimental paradigm is shown in Figure 5.10.

After the session, each participant completed the psychological questionnaires and rated the images using the SAM test [54]. The original results [251] for the assessment of images' arousal and valence were compared with the results obtained from the evaluations of study participants and are shown in Table 5.8.

Cross-Biofeedback Management The real-time biofeedback presentation required selecting a metric that could reflect participants' subjective perceptions and emotional states. Previous research has shown that frontal EEG asymmetry is a reliable index of the emotional responses [90]. For this preliminary analysis, the FAA was chosen as the neurofeedback index. FAA represents the relative difference in the activity of the alpha band (8–13 Hz) between the left and right frontal hemispheres. According to Metzen et al. (2022) [306], individual EEG alpha asymmetry can be quantified using the LQ, previously described in subsection 2.3.5.

In this study, the bipolar derivations Fp1-F7 and Fp2-F8 were used to compute the power difference. Positive LQ values indicate higher relative right alpha power (i.e., higher left cortical activity), while negative LQ values indicate the opposite. In this experimental protocol, the LQ value was computed in real-time and mapped to a colour scale to represent participants'

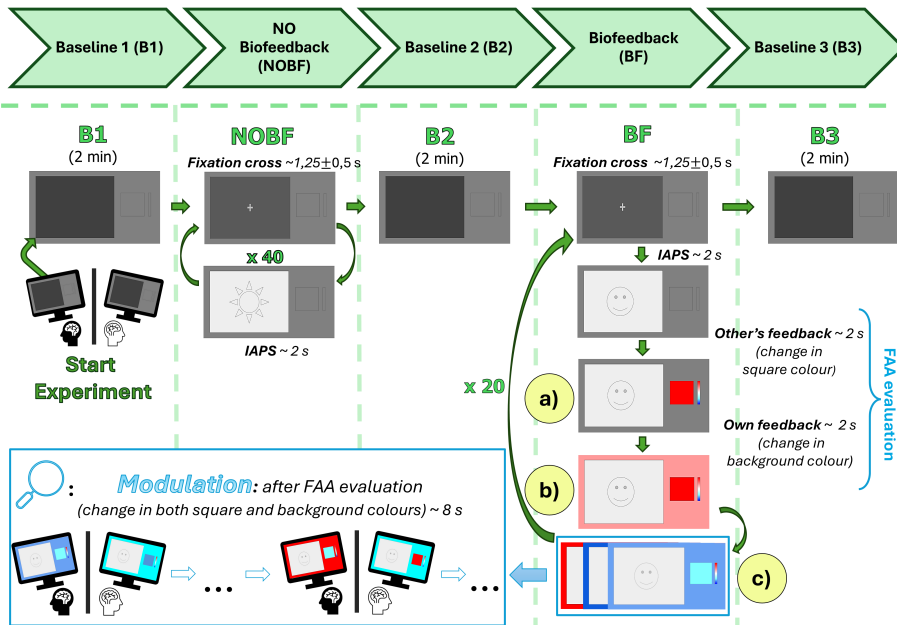


Figure 5.10: Experimental pipeline. The paradigm consisted of five consecutive phases: two stimulation phases (NOBF and BF) separated by three baselines (B1, B2, B3). B1, B2, and B3 columns show the 2-minute baseline interface displayed on the participants' monitor. The NOBF column illustrates the stimulation phase without biofeedback, with 40 IAPS images displayed for 2 seconds, each preceded by a fixation cross. The BF column represents the biofeedback phase, including 20 IAPS images followed by real-time visual feedback based on the EEG-derived metric (FAA). After each image, three sub-phases occur: (a) Other's feedback: the square changes colour to indicate other participants' response; (b) Own feedback: the background colour changes to reflect the participant's own response; (c) Modulation: both the square and the background colours dynamically change, providing cross-biofeedback that reflects the mutual interaction between participants.

Table 5.8: Comparison between the original assessment (IAPS) [250] and the assessment obtained through the SAM test administered to the participants (mean $\pm$ std) regarding the images delivered in the two conditions with and without biofeedback.

Phase	Domain	IAPS	SAM
No Biofeedback			
Low A - Low V	Valence	4.74 $\pm$ 0.53	4.19 $\pm$ 0.76
	Arousal	3.01 $\pm$ 0.67	2.57 $\pm$ 0.52
Low A - High V	Valence	7.27 $\pm$ 0.80	6.74 $\pm$ 0.73
	Arousal	3.48 $\pm$ 0.62	2.56 $\pm$ 0.37
High A - Low V	Valence	2.04 $\pm$ 0.29	1.58 $\pm$ 0.42
	Arousal	6.73 $\pm$ 0.70	5.58 $\pm$ 0.59
High A - High V	Valence	7.49 $\pm$ 0.80	6.73 $\pm$ 0.80
	Arousal	5.69 $\pm$ 0.79	3.29 $\pm$ 0.76
Biofeedback			
Low A - Low V	Valence	4.67 $\pm$ 0.42	4.15 $\pm$ 0.60
	Arousal	3.49 $\pm$ 0.69	2.62 $\pm$ 0.66
Low A - High V	Valence	6.60 $\pm$ 0.57	6.24 $\pm$ 0.29
	Arousal	3.30 $\pm$ 0.15	2.37 $\pm$ 0.33
High A - Low V	Valence	2.04 $\pm$ 0.29	1.64 $\pm$ 0.32
	Arousal	6.75 $\pm$ 0.35	5.59 $\pm$ 0.33
High A - High V	Valence	7.09 $\pm$ 0.45	6.32 $\pm$ 0.70
	Arousal	6.46 $\pm$ 1.07	4.22 $\pm$ 0.66

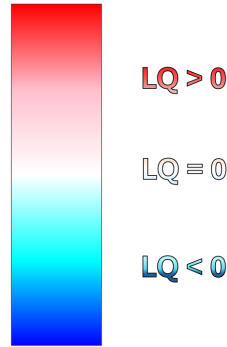


Figure 5.11: Colour scale reflecting LQ values based on participants' emotional responses.

emotional response (Figure 5.11). Positive emotions and approach-related behaviour were associated with positive LQ values and shades of red. In contrast, negative emotions and avoidance-related behaviour were related to negative LQ values and shades of blue [110] [90].

Statistical analyses of FAA across the experimental phases are described in section 5.3.2.

Synchronisation Feature Extraction After visual inspection of the recordings, data from 20 dyads were selected, while five dyads were excluded due to excessive noise. Signal preprocessing consisted of band-pass filtering (FIR, 1-45 Hz, order 600), the artifact removal phase using ICA, and signal re-referencing using CAR. The analysis of synchronisation was achieved through the PLV, which was selected as a measure of phase synchrony and represents an indicator of neural coupling. Within a defined time window, the phase difference between pairs of EEG electrodes is calculated [32], as described in subsection 2.3.5. In this study, differences were computed between homologous electrodes of the two participants in each dyad (e.g., Fp1 of subject A with Fp1 of subject B).

For each participant, the signal was divided into five macro-events:

- B1: first baseline;
- NOBF: images-presentation phase without biofeedback;
- B2: second baseline;

- BF: images-presentation phase with biofeedback;
- B3: third and last baseline.

Each macro-event was split into 2-second sub-windows with a 0.5-second overlap, and each sub-window was normalised with a z-score. A downsampling procedure was applied to reduce contributions from high frequencies not typically associated with EEG activity. The downsampling consisted of averaging every five consecutive samples. For each dyad, the PLV values were calculated within each time window, and a mean PLV value was obtained for each electrode pair across dyads. Moreover, ΔPLV was computed for each EEG channel as the difference between the median PLV of the two phases included in the comparison (for example, for the NOBF vs BF comparison: $\Delta\text{PLV} = \text{median}(\text{PLV_NOBF}) - \text{median}(\text{PLV_BF})$).

Statistical Analysis Three main research questions were formulated and tested through statistical analysis. The first addressed whether IBS, quantified using the PLV, differed across experimental phases. In particular, the aim was threefold: (i) to determine whether synchronisation changes between phases with and without neurofeedback, (ii) to investigate whether dyad familiarity (familiar vs. unfamiliar dyads) modulates this synchronisation, and (iii) to assess whether the observed effects reflected genuine interaction between partners or random EEG fluctuations. The second question concerned the neurofeedback metric used in the experimental design, i.e., the FAA. Specifically, the study aimed to determine whether FAA, which generates the biofeedback signal, varied significantly across phases, thereby testing its reliability and sensitivity as a feedback parameter. Furthermore, possible links between the FAA and PLV have been investigated. In particular, PLV was compared with a dissimilarity index FAA_{ratio} derived from the dyads' FAA. The third question investigated whether individual psychometric characteristics (e.g., empathy, emotional contagion, and social anxiety) were related to IBS. For this purpose, a correlation analysis was performed between participants' psychometric scores and their mean PLV values across phases.

Synchronisation Analysis To address the first research question, PLV values were averaged across participants for each channel and compared across experimental phases. The Shapiro-Wilk test was used to assess whether

the data followed a normal distribution. If normality was confirmed, the parametric t-test was applied; otherwise, the non-parametric Wilcoxon signed-rank test was employed. To compare the PLV values in the NOBF phase itself, NOBF was divided into two sub-phases: $NOBF_1$, which contains the first half, low arousal images, and $NOBF_2$, which contains the second half, high arousal images. The same choice was made for the BF phase, which was divided into BF_1 and BF_2 .

Statistical analysis, with a level of significance equal to 0.05, was performed to compare the following conditions:

- NOBF vs BF (both normalised for the PLV values obtained in B1 by subtracting them sample by sample and channel by channel)
- $NOBF_1$ vs $NOBF_2$ (both normalised by B1)
- BF_1 vs BF_2 (both normalised by B1)
- B1 vs B2
- B1 vs B3
- B2 vs B3 (both normalised by B1)

Comparisons between stimulation (NOBF and BF) and baseline phases (B2 and B3) were also computed (see Table 5.10), with all comparisons performed on series normalised with respect to B1. Owing to the balanced composition of the sample (10 familiar and 10 unfamiliar dyads), it was possible to evaluate whether PLV differed significantly between the two sub-groups across the experimental phases. Following normalisation with respect to the first baseline (B1) and after evaluating the distribution of the data with the Shapiro-Wilk test, the parametric two-sample t-test was employed, and ΔPLV was calculated. For each channel, ΔPLV is defined as the difference between the median PLV in the familiar condition and the median PLV in the unfamiliar condition.

To assess whether the observed synchronisation could be explained by random factors, a surrogate analysis was performed. Following established approaches [32] [268] [354], participants were randomly paired to create 760 artificial dyads, forming the surrogate group. The PLV values of these surrogate pairs represent a random-level synchronisation [32]. PLV was then calculated for the surrogate group, and values were compared with those of the real dyads across experimental phases. After confirming the non-normal

distribution of the data using the Shapiro-Wilk test, differences were tested using the non-parametric Mann-Whitney U test.

Frontal Alpha Asymmetry Analysis To test the second research question, the analysis focused on the asymmetry index across experimental phases. FAA was calculated for each subject and each phase using 2-second windows with a 0.5-second overlap. Before statistical analysis, FAA data underwent some preprocessing steps. Firstly, data were normalised with respect to the initial baseline (B1), which was subsequently excluded from further statistical analyses. Then, outliers were identified and excluded by removing values greater than three scaled MAD from the median. For each participant and experimental phase, the median and iqr were computed to assess both tendency and variability of the FAA values. After verifying the non-normal distribution of both median and iqr values, the non-parametric Friedman test was used to analyse differences across phases, followed by Bonferroni-corrected post hoc pairwise comparisons.

Finally, to examine associations between FAA and the synchronisation index, the previously computed PLV was considered for further analysis. PLV was calculated across 16 EEG channels using a CAR. Because FAA was computed at the individual level and PLV at the dyadic level, an asymmetry index, FAA_{ratio} , was defined as in Equation 5.1:

$$FAA_{ratio}(i) = \frac{\max_{FAA}(i)}{\min_{FAA}(i)} \quad (5.1)$$

Where $\max_{FAA}(i)$ and $\min_{FAA}(i)$ are the highest and lowest FAA values within the i -th dyad. This index quantifies FAA dissimilarity between dyad members: values closer to 1 indicate greater similarity, while higher values indicate divergence. Correlations between FAA_{ratio} and PLV were assessed for each experimental phase (with the BF phase divided into BF_{IMM} and BF_{MOD} , corresponding to stimulus presentation and modulation periods). Depending on the data distribution, as determined by the Shapiro-Wilk test, either Pearson's or Spearman's correlation was applied.

PLV Correlation with Psychometric Scores To test whether individual psychometric traits correlate with neural synchrony, the third statistical analysis was conducted. For each dyad and each experimental phase, a mean PLV was obtained by averaging values across the temporal windows within that phase. Since each participant was recorded using 16 EEG electrodes,

16 mean PLV values were initially derived per dyad. For the final analysis, only electrodes T3, T4, T5, T6, P3, P4, O1, and O2 were retained, based on surrogate analysis results that identified regions where synchronisation effects were statistically significant and unlikely due to random fluctuations (see further subsection 5.3.3). The mean PLV across these electrodes was then computed to yield a single IBS index for each dyad and phase.

Psychometric data (Table 5.7) were analysed with a generalised linear model (GLM), implemented in MATLAB using the *fitglm* function, to examine associations between psychometric traits and PLV. The model was defined as follows (using Wilkinson notation) in Equation 5.2:

$$Y \sim 1 + K_1 + K_2 \quad (5.2)$$

Where Y is a Gaussian-distributed variable representing the PLV value of the dyad in the given condition, and 1 denotes the intercept. The index $K_1 = (V_{\max} + 1)/(V_{\min} + 1)$ quantifies the intra-dyadic difference in test scores, reflecting divergence between the two participants. Higher K_1 values indicate greater disparity, while values near 1 indicate greater similarity. Adding +1 to both numerator and denominator normalises the index for tests with a minimum score of zero (e.g., SIAS and SPS), preventing division by zero. The index $K_2 = (V_{\max} + V_{\min})/TOT_{\text{test}}$ captures the absolute level of the psychological trait expressed by the dyad, scaled to the test's maximum achievable score. Higher K_2 values indicate higher overall scores within the pair.

5.3.3 Results

Results are presented according to the three main hypotheses outlined in the statistical analysis section 5.3.2. Regarding the analysis of synchronisation metrics during the different phases of the experiment, results from comparisons between the various stimulation phases and between the different baseline phases are reported in the Table 5.9, along with the associated p-value and the corresponding ΔPLV . The stimulus phases (i.e., NOBF and BF) were further subdivided into sub-phases according to the arousal level of the images presented: $NOBF_1$ and BF_1 comprising low-arousal images, whereas $NOBF_2$ and BF_2 comprising high-arousal images.

Comparisons between stimulation and baseline phases are presented in Table 5.10, with the associated p-value and the corresponding ΔPLV .

Table 5.9: Comparisons between the different stimulation phases and between the different baseline phases.

Comparison	Channel	p-value	Δ PLV
NOBF vs BF	T3	0.0087	0.0025
	C3	0.0109	0.0048
	C4	0.0144	0.0002
	T5	0.0147	0.0017
	P4	0.0125	0.0017
	O1	0.0444	0.0004
NOBF ₁ vs NOBF ₂	Fp2	0.0420	-0.0023
	F3	0.0214	-0.0054
BF ₁ vs BF ₂	F8	0.0329	-0.0066
	T4	0.0284	-0.0029
	P4	0.0049	-0.0041
B1 vs B2	C4	0.0309	-0.0044
B1 vs B3	T3	0.0393	-0.0048
	C4	0.0218	-0.0043
	T6	0.0284	-0.0072

Specifically, in comparison between NOBF and BF phases (Table 5.9), the mean PLV was found to be higher during the phase without biofeedback (NOBF). Significant results emerged for the NOBF vs BF comparison in temporal (T3, T5), central (C3, C4), parietal (P4), and occipital (O1) electrodes, indicating involvement of centre-posterior scalp areas.

Two significant results emerged when comparing the two sub-phases of the NOBF phase itself, indicating an increase in mean PLV for electrodes Fp2 and F3 during the phase. Also, an increase in mean PLV was observed in the BF phase itself (BF1 vs BF2), particularly in channels F8, T4, and P4.

A PLV increase was also observed in the first and second baseline comparisons for electrode C4, with a further increase detected in the comparison with the final baseline, where the mean PLV was again higher in channel C4, as well as in T3 and T6. No results emerged for the B2 and B3 comparisons.

About the comparisons between the stimulation phases (NOBF, BF) and the post-initial baseline phases (B2, B3), the results are presented in Table 5.10. Statistically significant findings and consistently positive Δ PLV values indicate that stimulation phases are associated with higher mean PLV than baseline phases. This effect was observed across a large number of EEG channels, suggesting widespread scalp distribution.

In the comparison between familiar and unfamiliar dyads, a significant effect was found at electrode C4 during the final baseline (p-value = 0.0376;

Table 5.10: Comparisons between stimulation (NOBF and BF) and baseline phases (B2 and B3). All comparison were performed on series normalised with respect to B1

Comparison	Channel	p-value	Δ PLV
NOBF vs B2	Fp1	0.0036	0.0040
	Fp2	0.0160	0.0029
	F7	0.0053	0.0037
	F4	0.0068	0.0051
	T3	0.0194	0.0033
	C3	0.0025	0.0060
	T5	0.0287	0.0026
	P4	0.0024	0.0058
	T6	0.0046	0.0064
	O1	0.0016	0.0027
	O2	0.0005	0.0089
NOBF vs B3	Fp1	0.0121	0.0033
	F7	0.0085	0.0069
	F4	0.0044	0.0056
	P4	0.0026	0.0056
	T6	0.0034	0.0030
	O2	0.0008	0.0104
BF vs B2	Fp1	0.0014	0.0031
	Fp2	0.0004	0.0057
	F7	0.0003	0.0037
	F4	0.0132	0.0042
	O1	0.0145	0.0023
	O2	0.0012	0.0075
BF vs B3	Fp1	0.0047	0.0025
	Fp2	0.0092	0.0023
	F7	0.0013	0.0068
	F4	0.0285	0.0046
	O2	0.0004	0.0090

Δ PLV=0.0042) indicating different synchronisation in familiar pairs. During the NOBF phase, further significant effects were observed at electrodes Fp2 (p-value = 0.0412, Δ PLV = 0.0086), F3 (p-value = 0.0363, Δ PLV = 0.0090), and T5 (p-value = 0.0376, Δ PLV = 0.0091), again indicating different synchronisation in familiar dyads.

Regarding the comparison between real and surrogate dyads, significant results were observed in the central, temporal, parietal, and occipital channels. As reported in Table 5.11, Δ PLV values were generally positive, indicating higher synchronisation in real dyads compared to surrogates.

Table 5.11: Table of p-values and Δ PLV for each channel and phase in real vs surrogates comparisons.

Channel	Phase	p-value	Δ PLV	Channel	Phase	p-value	Δ PLV
T3	B1	0.0084	0.0065	P4	B1	0.0020	0.0079
	NOBF	0.0003	0.0089		NOBF	p<0.001	0.0075
	B2	0.0047	0.0062		B2	0.0347	0.0051
	BF	0.0064	0.0041		BF	p<0.001	0.0094
	B3	0.0015	0.0086		B3	0.0064	0.0083
	BF_1	0.0227	0.0035		BF_1	0.0003	0.0056
	BF_2	0.0257	0.0040		BF_2	p<0.001	0.0091
	$NOBF_1$	0.0027	0.0088		$NOBF_1$	p<0.001	0.0089
	$NOBF_2$	0.0012	0.0101		$NOBF_2$	p<0.001	0.0079
C3	NOBF	0.0149	0.0055	T6	B1	0.0054	0.0043
	$NOBF_1$	0.0038	0.0080		NOBF	p<0.001	0.0085
C4	NOBF	0.0481	0.0037		B2	0.0107	0.0066
					BF	p<0.001	0.0099
T4	NOBF	0.0072	0.0037		B3	0.0006	0.0090
	BF	0.0325	-0.0006		BF_1	p<0.001	0.0075
	BF_2	0.0173	-0.0006		BF_2	p<0.001	0.0125
	$NOBF_2$	0.0028	0.0040		$NOBF_1$	0.0006	0.0094
T5	B1	0.0147	0.0067		$NOBF_2$	p<0.001	0.0105
	NOBF	0.0001	0.0098	O1	B1	0.0073	0.0053
	B2	0.0061	0.0080		NOBF	p<0.001	0.0093
	BF	0.0002	0.0075		B2	0.0146	0.0055
	B3	0.0072	0.0101		BF	p<0.001	0.0087
	BF_1	0.0020	0.0048		B3	0.0038	0.0068
	BF_2	0.0003	0.0084		BF_1	0.0002	0.0083
	$NOBF_1$	0.0001	0.0101		BF_2	p<0.001	0.0097
	$NOBF_2$	0.0035	0.0079		$NOBF_1$	p<0.001	0.0124
P3	B1	0.0015	0.0138		$NOBF_2$	0.0002	0.0097
	NOBF	p<0.001	0.0104	O2	NOBF	0.0069	0.0058
	B2	0.0023	0.0093		BF	0.0111	0.0060
	BF	p<0.001	0.0114		BF_1	0.0161	0.0052
	B3	0.0004	0.0094		BF_2	0.0039	0.0072
	BF_1	p<0.001	0.0116		$NOBF_1$	0.0087	0.0041
	BF_2	p<0.001	0.0100		$NOBF_2$	0.0246	0.0089
	$NOBF_1$	0.0004	0.0108				
	$NOBF_2$	p<0.001	0.0111				

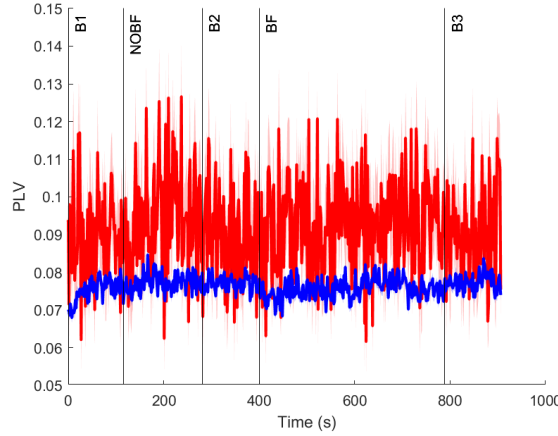


Figure 5.12: Real dyads (red) and surrogate (blue) PLV trend across the experimental phases for channel P3, which showed a significant difference in statistical analysis.

To visually assess potential differences between surrogate and real dyads, their trends were superimposed in a single plot for each channel. Specifically, a visual representation of PLV trends has been generated by averaging PLV values for each window across all subjects. Moreover, the data from all phases were concatenated obtaining the PLV trend for each channel across the five experimental phases (B1, NOBF, B2, BF, B3) covering the whole duration of the experiment. The Figure 5.12 illustrates the PLV trend across experimental phases for a channel (P3), which exhibited a significant difference between real dyads and surrogate pairs.

Additionally, Figure 5.13 represents the distribution of PLV values for surrogate and real dyads across the experimental phases for the same channel (P3).

Concerning the evaluation of FAA values across the experimental phases, the statistical analysis revealed significant differences in the Interquartile Range of the FAA values. Results of the analysis are reported in the Table 5.12. It is noteworthy that no significant differences in median FAA values were found across phases.

Regarding the correlation between the dyadic asymmetry index (FAA_{ratio}) and PLV, the results revealed several significant associations. In the NOBF

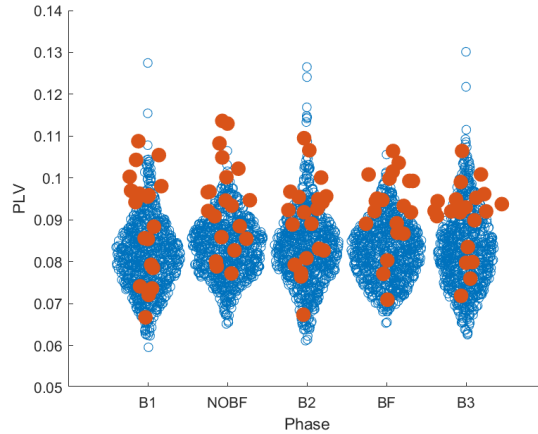


Figure 5.13: Real dyads (red) and surrogate (blue) PLV distribution across the experimental phases for channel P3.

phase, significant negative correlations were observed using Spearman's method at channels T4 ($R = -0.486$, $p = 0.0315$) and P4 ($R = -0.508$, $p = 0.0236$). During the B3 phase, Pearson's correlation indicated significant positive associations at channels Fp1 ($R = 0.458$, $p = 0.0422$) and O1 ($R = 0.551$, $p = 0.0119$). The significant results of the statistical analysis comparing psychometric scores and mean PLV for each couple are shown in Table 5.13.

For the K1 index (internal asymmetry within the couple), the TAS 20 showed a significant negative correlation at various stages (e.g., NOBF, BF_2), indicating that greater heterogeneity (i.e., higher K1 values) in alexithymia levels between partners is associated with lower neural synchrony.

For the K2 index (absolute couple score), total empathy (QCAE) was found to be negatively correlated with PLV during the stimulus phases (NOBF, BF_1), suggesting that higher overall levels of empathy are associated with reduced phase synchrony; this is a counterintuitive finding, but it is consistent with the absence of couples with extreme empathy levels (see Table 5.7). No significant results emerged for SIAS and SPS.

Table 5.12: Post-hoc comparisons for iqr of the FAA values between experimental phases.

Phase 1	Phase 2	Lower CI	E.D.	Upper CI	p-value
NOBF	B2	0.1634	0.9250	1.6866	0.0081
NOBF	BF	-0.7366	0.0250	0.7866	N.S.
NOBF	B3	-0.5116	0.2500	1.0116	N.S.
B2	BF	-1.6616	-0.9000	-0.1384	0.0109
B2	B3	-1.4366	-0.6750	0.0866	N.S.
BF	B3	-0.5366	0.2250	0.9866	N.S.

CI: Confidence Interval
E.D.: Estimated Difference
N.S.: Not Significant

Table 5.13: GLM estimates and significance for K1 (asymmetry) and K2 (absolute couple score) by phase and test. TAS: Toronto Alexithymia Scale, EmpTot: Total Empathy (QCAE).

phase	Test	K1 Estimate (SE*)	K1 p-value (tStat)	K2 Estimate (SE*)	K2 p-value (tStat)
B1	TAS	-0.0343 (0.0150)	0.0357 (-2.2804)	/	NS**
BF.2	TAS	-0.0284 (0.0130)	0.0432 (-2.1843)	/	NS
NOBF.2	TAS	-0.0409 (0.0187)	0.0433 (-2.1837)	/	NS
NOBF	TAS	-0.0349 (0.0163)	0.0477 (-2.1338)	/	NS
NOBF.2	EmpTot	/	NS**	-0.2799 (0.0667)	0.0006 (-4.1975)
NOBF	EmpTot	/	NS	-0.2304 (0.0589)	0.0011 (-3.9113)
NOBF.1	EmpTot	/	NS	-0.1754 (0.0642)	0.0142 (-2.7312)
BF.1	EmpTot	/	NS	-0.1299 (0.0567)	0.0351 (-2.2902)

* Standard Error, ** Not Significant

5.3.4 Discussions

EEG Hyperscanning with biofeedback provides novel insights into the neural mechanisms underlying emotional processing in social contexts. This methodological advancement offers a promising avenue for elucidating the complexities of human social interaction and emotional cognition. Building on the introduction of this methodology, the present study addresses three primary research questions and their potential interpretations.

The first analysis examined IBS, quantified via PLV, to assess variation across experimental phases, the influence of interpersonal familiarity, and differences from random EEG activity. The second test evaluated the reliability and sensitivity of FAA as a biofeedback metric across phases and sub-phases of the biofeedback phase itself). The third line of analysis investigated associations between individual psychometric traits, such as empathy, alexithymia, and social anxiety, and IBS, as measured by correlations with PLV values. The hypothesis was that neural synchronisation would increase during the BF phase, reflecting greater mutual awareness between participants, in line with prior findings of enhanced IBS during cooperative and communicative tasks. Contrary to this hypothesis, the PLV comparison showed no clear increase in synchronization across phases. Notably, the NOBF phase, which preceded biofeedback, exhibited higher mean PLV values than the first biofeedback sub-phase (BF_1); these differences, seen over centro-posterior electrodes, remained significant when comparing NOBF with the second sub-phase (BF_2) for the left centro-temporal region. A direct comparison between BF_1 and BF_2 revealed a significant increase in mean PLV during the latter, indicating a progressive enhancement of neural synchronisation within the biofeedback phase. These findings suggest that the preceding 2-minute baseline of BF_1 may have acted as a reset, temporarily disrupting interpersonal phase alignment and initially reducing synchronisation. This alignment was subsequently recovered during the BF_2 phase. Baseline data support this interpretation, as PLV increased between the first and final baseline at electrodes T3, C4, and T6, indicating a gradual enhancement of synchronisation across the experiment (Table 5.9). Alternatively, this pattern may be attributable to the complexity of the task or the emergence of an emotional attunement period.

Interpersonal familiarity yielded limited effects. Notably, significant differences appeared at electrode C4 in the final baseline (p-value = 0.0376, ΔPLV = 0.0042) and at electrodes Fp2 (p-value = 0.0412, ΔPLV = 0.0086), F3 (p-value = 0.0363, ΔPLV = 0.0090), and T5 (p-value = 0.0376, ΔPLV = 0.0091) during the NOBF phase; familiar dyads consistently showed higher PLV values. These findings suggest the familiar/unfamiliar distinction alone may not strongly impact neural synchronisation, matching earlier reports that only long-term pre-existing relationships drive substantial IBS enhancements rather than mere acquaintance [123].

To further validate these results, the surrogate analysis confirmed the

reliability of the observed neural coupling patterns, as real dyads consistently exhibited higher PLV values than surrogate pairs across the entire experiment (Table 5.11). Significant effects were particularly evident over temporo-parietal and occipital electrodes (T3, T4, T5, T6, P3, P4, O1, O2), with additional contributions from central sites (C3, C4), especially during the NOBF phase. This spatial distribution aligns with previous findings indicating that temporo-parietal regions are deeply involved in interpersonal neural synchronisation, supporting dynamic coupling between individuals engaged in social or affective exchanges. From a functional perspective, the temporo-parietal junction (TPJ) emerges as a critical hub within this network. Situated at the intersection of the temporal and parietal lobes, the TPJ has been repeatedly implicated in social cognition, empathy, and emotional contagion. It plays a pivotal role in differentiating between self- and other-related representations, a process essential for mature empathy, which involves understanding and resonating with another's emotional state without losing one's own self-boundaries [192]. The TPJ also integrates sensory and contextual information to construct a coherent model of others' intentions and emotions, while modulating automatic emotional responses such as mimicry depending on social context (e.g., in-group vs. out-group interactions). The superior temporal sulcus (STS) also plays a key role by rapidly decoding social cues such as body movement, facial expressions, and eye gaze, which serve as primary signals for emotional contagion. Together, the TPJ and STS form a distributed network that integrates perception and emotion in social behavior. Their concurrent activation in this study suggests that interpersonal synchronisation arises from the interaction of perceptual, affective, and cognitive processes central to human connection. These findings strongly suggest neural coupling is no passive echo. Instead, it emerges as an active, interactive interplay, powered by higher-order cortical regions wired for decoding others and sharing in emotional experience.

The comparison between real and surrogate dyads revealed differences in PLV dynamics. As shown in Figure 5.12, which presents PLV trends across phases for channel P3, real dyads exhibited greater amplitude fluctuations than surrogate dyads. This finding suggests stronger and more variable phase synchronisation in real interactions, likely reflecting authentic social and neural coupling processes absent in surrogate pairs. Figure 5.13 illustrates the PLV distribution across phases, further confirming that real dyads consistently exhibit higher PLV values than surrogate pairs (Figure 5.12). This

finding raises important considerations about the necessity of real sensory interaction and the complexity of social biological perception. Real sensory interaction drives genuine neural coupling. The difference between real and surrogate pairs demonstrates that authentic IBS requires actual sensory exchange between individuals, shared emotional stimuli, and mutual awareness. The greater amplitude fluctuations in real dyads suggest that social interaction involves dynamic neural processes that continuously adapt. Neural synchrony reflects genuine social processes. This evidence supports the hypothesis that IBS can serve as an objective neural marker of social interaction and empathic engagement.

Analysis of FAA revealed significant differences only for the iqr, indicating that the iqr, but not the median, was sensitive to stimulus-driven variability. Significant effects were found between stimulation phases (NOBF, BF) and the central baseline (B2), but not between the two stimulation conditions, suggesting that biofeedback did not modulate FAA. Correlation analyses between FAA_{ratio} and PLV showed a negative association during NOBF at P4 and T4, indicating that greater asymmetry dissimilarity corresponded to reduced IBS. In contrast, positive correlations during the final baseline (B3) at Fp1 and O1 suggested a shift in coupling following biofeedback exposure. These results question the suitability of FAA as a biofeedback index, suggesting limited sensitivity to rapid affective changes in interactive contexts despite its established associations with emotional valence and regulation.

The patterns observed in this study led to explore alpha asymmetry beyond frontal regions, extending the analysis to other areas of the scalp. While frontal alpha asymmetry is widely used to assess inter-hemispheric differences in cortical activity, particularly concerning approach/withdrawal motivation and affective processing [112], recent studies [234,306] have also emphasized parietal alpha asymmetry (PAA). PAA appears to be linked to emotional regulation, especially in affective disorders and arousal-related activation patterns. This finding may also relate to brain areas that are highly engaged in emotional-social coupling.

Statistical analysis revealed significant associations between IBS, measured by PLV, and psychometric scores, particularly alexithymia and dispositional empathy. For alexithymia, Table 5.13 shows that the K1 index (quantifying intra-dyadic divergence) was negatively correlated with PLV, suggesting that larger discrepancies in TAS-20 scores between dyad members are associated with reduced synchronization. This effect was most pro-

nounced during stimulus-processing phases (NOBF, $NOBF_2$, BF_2), but was also observed in the initial baseline (B1). These results provide strong evidence that discrepancies in emotional processing between dyad members are associated with reduced interpersonal synchrony, which is often underpinned by neural mechanisms. This finding is consistent with the work of Matsumoto et al. (2006) [295], who reported reduced gamma synchronisation in alexithymic individuals exposed to emotional stimuli, interpreted as a deficit in affective resonance and emotion regulation mechanisms. The latter is the only condition that shows early significance (before emotional stimulation) and could be interpreted as an effect of procedural stress (e.g., electrode placement), which may have elicited shared anticipatory responses not directly linked to the interaction.

Regarding empathy, the K2 index (reflecting the dyad's absolute empathy level) also showed a significant negative correlation with PLV. Higher levels of absolute empathy were associated with lower IBS. Although counterintuitive, this effect may be attributable to the restricted distribution of test scores, with no participants showing extreme empathy values. This result partially aligns with findings from Falcon et al. (2024) [146], who showed that dispositional empathy modulates IBS, particularly in the beta frequency band, which is implicated in shared cognitive processing. The present findings also corroborate those of Schwartz et al. (2025) [387], who demonstrated that IBS can emerge even in the absence of overt social interaction, driven solely by the shared perception of emotionally salient stimuli. In their work, synchronisation is proposed as a neural marker of empathy, capable of objectively detecting and quantifying empathic engagement. This result partially aligns with Falcon et al. (2024) [146], who found that dispositional empathy modulates IBS, particularly in the beta band. It is also supported by Schwartz et al. (2025) [387], who demonstrated that synchrony can arise from shared emotional stimulation even without direct interaction, suggesting it as a neural marker of empathy. The current study supports this hypothesis [387] and further suggests that the quality of synchrony depends not only on individual empathy levels but also on the psychological characteristics within the dyad. These results suggest that IBS is shaped not only by individual traits (e.g., individual empathy or alexithymia) but also by their distribution within the dyad (e.g., the degree of divergence in alexithymia between partners). This highlights the importance of considering psychometric profiles as potential criteria for dyad selection or matching

in future studies, rather than treating them solely as auxiliary variables.

5.4 Conclusions

This chapter examined psychophysiological dynamics in affective, social, and interactive contexts, extending the scope of the thesis beyond individual perceptual and cognitive processing toward relational and context-dependent phenomena. Across three complementary experimental paradigms, the results converge in showing that emotional meaning and social co-presence introduce additional layers of organization in neural and autonomic activity, which cannot be fully explained by stimulus properties or task structure alone. A first contribution of this chapter lies in demonstrating that affective processing is strongly shaped by individual dispositions when emotional meaning is central. The neuroaesthetic study shows that traits linked to knowledge-based processing and affective resonance modulate neural dynamics at different temporal stages, highlighting a dissociation between early, expertise-driven reconfiguration and later, emotion-dependent evaluative processes. These findings reinforce the idea that affective experience is not a unitary phenomenon but unfolds through temporally structured neural mechanisms that reflect both cognitive schemas and emotional sensitivity. Within the broader framework of the thesis, this supports the view that psychophysiological markers identified in controlled settings remain informative in richer contexts, while being selectively reshaped by personal and affective factors. A second contribution concerns the transition from individual to shared emotional experience. The dyadic EDA study demonstrates that even in the absence of explicit interaction, simultaneous exposure to affective stimuli can elicit partially aligned autonomic dynamics across individuals. While substantial inter-subject variability persists, the presence of convergent EDA patterns in some dyads suggests that emotional co-presence alone may be sufficient to induce passive forms of physiological coupling. This finding bridges individual affective responses and social neuroscience by indicating that shared emotional contexts can act as a minimal social scaffold, upon which more explicit interpersonal dynamics may later emerge. The third study further extends this perspective by explicitly targeting interpersonal neural coupling under emotionally salient stimulation and cross-biofeedback. Hyperscanning results indicate that IBS reflects genuine relational processes rather than mere stimulus-driven correlations, as supported by comparisons

with surrogate dyads. Importantly, the absence of a uniform increase in synchrony across experimental phases underscores that social neural coupling is not a simple by-product of interaction or feedback, but a dynamic phenomenon shaped by temporal adaptation, task structure, and the psychological composition of the dyad. The observed associations between IBS and traits such as empathy and alexithymia further emphasize that interpersonal dynamics are modulated not only by individual characteristics, but also by their distribution within interacting pairs. Importantly, it should be noted that in the hyperscanning experiment reported in section 5.3, this time the EEG preprocessing pipeline did not rely on the HAPPE framework [164]; instead, a dedicated workflow was adopted that retained only the essential steps required for artifact reduction and signal cleaning. This approach was motivated by the use of a wet-electrode EEG system, which typically provide higher baseline SNR than dry-electrode setups and therefore allow for more conservative preprocessing strategies. Particular care was taken to avoid excessive preprocessing operations that could overprocess the signal and introduce distortions or misinterpretations in the connectivity metrics subsequently extracted. To further control for methodological variability, analyses also included comparisons between real dyads and surrogate pairings, enabling a clearer distinction between stimulus-driven correlations and interpersonal coupling. That said, this chapter highlights a progressive shift in psychophysiological organization as experimental contexts become affectively and socially enriched. Neural and autonomic responses evolve from predominantly intra-individual patterns toward configurations that reflect shared meaning, mutual adaptation, and relational alignment. This progression is fully consistent with the overarching objectives of the thesis: to identify psychophysiological markers across contexts, to assess the value of dynamic and connectivity-based methodologies, and to integrate multimodal information within coherent interpretative frameworks. In conclusion, this chapter positions affective and social interaction as critical dimensions for understanding human psychophysiology. Emotional and relational factors do not merely amplify previously observed mechanisms, but reorganize them, revealing new forms of temporal coordination within and between individuals.

Chapter 6

Conclusion

6.1 Summary of contribution

The work presented in this dissertation has examined how cognitive, emotional and social processes emerge from the coordinated dynamics of neural, autonomic and behavioral systems, across a set of paradigms that progressively increase in ecological and interpersonal complexity. The thesis was conceived as a coherent investigation, starting from controlled perceptual and lexical tasks, moving through interactive game based environments, and culminating in dyadic hyperscanning with emotionally salient stimuli and cross biofeedback. Rather than treating these domains as disconnected, the dissertation has articulated how similar organisational principles recur across them, and how multimodal physiological signatures can be leveraged to characterise internal states in a principled way.

At the outset, chapter 1 formulated three overarching objectives. The first was to investigate neurophysiological and behavioral correlates of emotional and cognitive processes in controlled yet diverse experimental settings, so as to disentangle robust mechanisms from task specific modulations. The second was to adopt and critically evaluate advanced analytical methodologies for physiological time series, particularly those sensitive to temporal structure and intrinsic dynamics, such as functional connectivity, entropy and other nonlinear measures. The third was to pursue a multimodal perspective, integrating neural, autonomic and behavioral information within coherent analytical frameworks. The core chapters of this thesis address these aims through complementary lenses, and their combined contribution

exceeds the sum of their individual findings.

chapter 3 focused on the discrimination between natural and non natural, and semantic and non semantic, forms of information in controlled environments with minimal demands placed on participants. The study presented in section 3.1 on face perception showed that real and AI generated faces, even when carefully matched for emotional expression, elicit partially distinct EEG dynamics, suggesting that the nervous system remains sensitive to familiar versus unfamiliar inputs. This sensitivity is not exhausted by explicit affective content, but appears to reflect deeper evaluations concerning plausibility and relevance. The lexical paradigms presented in section 3.2, in which words and pseudowords with varying syllabic complexity were presented, further demonstrated that semantic availability and structural complexity shape the engagement of prefrontal and temporal networks, as indexed by the N400 component and associated spectral changes. Importantly, these effects emerged in a sample of young, neurotypical adults, indicating that even in the absence of overt pathology, EEG markers can reveal fine grained differences in language related processing. When autonomic and acoustic features were considered alongside EEG, additional layers of organisation became visible. EDA complexity measures and voice parameters, such as fundamental frequency and intensity, co varied with task demands and stimulus type, suggesting that sympathetic activation and vocal behaviour jointly encode aspects of cognitive load, discomfort and effort. In this way, chapter 3 provided an initial demonstration that cortical, autonomic and behavioral signals converge to differentiate meaningful or authentic stimuli from their synthetic or non semantic counterparts.

Building on this foundation, chapter 4 shifted attention to interactive, gamified settings that more closely approximate real world cognitive engagement. Here the central questions concerned how neural and autonomic markers reflect performance, attentional control, and emotional dynamics during ongoing visuomotor and memory based tasks. The chapter first presented the EEG study conducted on the Snake game (section 4.2), in which spectral profiles distinguished high from low performing participants. Low performers showed increased low frequency power in delta and theta bands, consistent with reduced attentional engagement and possible overload, whereas high performers exhibited increased alpha and beta activity, indicative of more efficient visuospatial updating and task focused processing. The chapter then examined pupillary dynamics during the Matching

Pairs game (section 4.3). Pupillometry revealed that even relatively simple serious games elicit measurable modulations of emotional state and resource allocation. Pupil dilation patterns reflected both subjective affective experience and performance related strategies, supporting the interpretation of pupil size as an integrated marker of cognitive effort and emotional involvement. Finally, section 4.4 addressed emotional expression and cardiovascular dynamics by analysing FEs and HRV during casual video game play in a culturally heterogeneous sample including participants from Italy, Korea and Japan. These results showed that emotional responses and autonomic regulation are jointly modulated by performance and game characteristics, and that sympathovagal balance adapts to cognitive load and task structure across different cultural backgrounds. The studies reported in this chapter illustrate how engagement emerges as an embodied phenomenon resulting from coordinated adjustments across neural, autonomic and expressive systems, and they support the potential use of multimodal markers in the design of adaptive serious games for assessment and training.

Finally, chapter 5 extended the scope of the dissertation to aesthetic and interpersonal dynamics. The chapter began with a neuroaesthetic study (section 5.3) in which functional connectivity, quantified through PLI, was analysed in individual participants exposed to visual artworks. This work demonstrated that aesthetic experience is associated with structured patterns of large scale neural coordination, providing a bridge between perceptual processing and higher order affective evaluation. The chapter then moved to the dyadic domain, first presenting an EDA hyperscanning study conducted during shared exposure to emotionally salient IAPS images (section 5.2). Synchronously recorded EDA signals revealed partially shared autonomic dynamics across individuals exposed to the same affective input. Although exploratory, this work provided a proof of concept for EDA based hyperscanning and highlighted the influence of arousal levels and subjective perception on both intra and inter individual structure. The final study of chapter 5 employed EEG hyperscanning to investigate how inter brain synchronisation unfolds in dyads viewing affective stimuli, with and without cross biofeedback (section 5.3). PLV analyses showed that inter brain coupling does not increase monotonically with the introduction of biofeedback, but evolves in a phase specific and time dependent manner. Synchronisation was generally higher in real dyads than in surrogate pairings, supporting the interpretation that the observed coupling reflects genuinely shared processing

rather than stimulus locked artefacts. Temporo parietal and occipital regions emerged as consistent hubs of synchrony, in line with their established roles in social cognition and the processing of emotionally salient visual information. Interpersonal familiarity exerted only limited effects, whereas psychometric traits such as alexithymia and empathy were more systematically related to synchronisation. Dyads characterised by larger intra pair differences in alexithymia tended to show reduced inter brain coupling, suggesting that disparities in emotional awareness and regulation hinder the establishment of shared neural dynamics.

Methodologically, the dissertation has contributed by systematically applying and integrating analytical tools tailored to the temporal and relational properties of physiological data. Functional connectivity metrics, entropy and other complexity measures applied to EEG, EDA, pupillary signals and voice, as well as correlation analyses linking psychometric indices to physiological dynamics, were used not as isolated techniques but as components of a coherent analytic strategy. These approaches revealed patterns of organisation that remain inaccessible to static or purely univariate descriptors. Moreover, the consistent use of multimodal recording setups, including dry electrode EEG systems combined with EDA, eye tracking and voice analysis, demonstrated the feasibility of deploying complex physiological monitoring in settings approaching ecological validity. In doing so, the thesis directly addressed the second and third objectives outlined in chapter 1, namely the evaluation of advanced analytical methodologies and the pursuit of multimodal integration.

Taken as a whole, the contributions of this dissertation can be summarised as follows. First, it has shown that contrasts between meaningful or authentic stimuli and their synthetic or non semantic counterparts are consistently reflected in coordinated changes across cortical and autonomic systems. Second, it has demonstrated that engagement and cognitive efficiency in interactive tasks are best understood through the joint analysis of neural oscillations, autonomic responses and behavioural or performance indices. Third, it has provided evidence that interpersonal synchronisation, indexed by both neural and autonomic measures, depends not only on shared stimulation but also on the psychological profiles and compatibility of individuals within a dyad. Finally, the dissertation has argued, both empirically and methodologically, for the value of a coherent, multimodal and dynamic approach to the study of human cognition, emotion and social interaction.

6.2 Cross cutting limitations and implications

Several limitations recur across the studies presented in this dissertation and should be considered when interpreting the findings and planning future developments. First, multiple experiments relied on relatively small sample sizes, which, although common in multimodal psychophysiology and hyper-scanning research, may limit statistical power and the stability of individual difference effects. Several studies relied predominantly on samples of young, neurotypical adults, which constrains the extent to which the observed patterns can be generalised across the lifespan and across clinical populations. Second, the demographic composition of the samples was often restricted, further limiting the breadth of population level inferences that can be drawn. Third, while an international cohort was included in the study reported in section 4.4, the overall cross cultural coverage of the dissertation remains limited, and cultural modulation of emotional expression, engagement and interpersonal synchrony cannot yet be fully characterised.

These cross cutting constraints have direct implications for the interpretation and extension of the present findings. In particular, the multimodal markers identified throughout the thesis should be considered preliminary with respect to broad population level generalisation, and their translational deployment will require systematic validation in larger and more heterogeneous cohorts. Larger samples would not only increase statistical power but also enable more fine grained analyses of individual differences, including age, gender, cultural background and clinical status. Cross cultural investigations will be especially valuable for disentangling universal from culture specific aspects of emotional expression, engagement and interpersonal synchrony. At the same time, the consistency of the observed patterns across paradigms suggests that the proposed analytical framework is sufficiently robust to warrant further scaling and refinement. Addressing these limitations therefore represents a necessary progression toward consolidating the external validity and applied potential of multimodal psychophysiology.

6.3 Directions for future work

The findings and methodological choices presented in this dissertation open several avenues for future research. These directions concern the refinement of analytical tools, the extension of experimental paradigms to broader and

more heterogeneous populations, the enhancement of ecological validity, and the translation of multimodal psychophysiological markers into applied and theoretically grounded contexts. Importantly, these perspectives are conceived not as departures from the present work, but as systematic extensions of its empirical and conceptual foundations.

A first set of developments pertains to the consolidation and expansion of the analytical framework adopted in this thesis. While the present work has employed functional connectivity, entropy and other nonlinear measures to capture temporal structure and interdependence in physiological signals, there remains substantial scope for refining and generalising these approaches. Future studies could benefit from the application of time resolved connectivity methods and dynamic network analyses, capable of tracking rapid changes in inter regional coupling during continuous tasks or social interactions. Such methods would provide a formal extension of the dynamic perspective already implicit in the analyses presented here. Similarly, cross frequency coupling metrics could yield additional insight into how oscillatory bands coordinate across cognitive and affective states, complementing the band limited analyses employed in the current studies.

For autonomic and behavioural signals, more advanced time series modelling approaches, including state space models and Bayesian or machine learning based techniques, could be used to infer latent states and transitions that are not directly observable in extracted features. Rather than replacing traditional descriptive or nonlinear metrics, these models would offer a principled framework for formalising the dynamics that the present thesis has characterised empirically. This would be particularly valuable in hyperscanning contexts, where the central question concerns how the physiological dynamics of two or more individuals become coupled, decoupled or reorganised over time. In this regard, the integration of dynamic modelling with surrogate data generation and permutation based inference would further strengthen the robustness of conclusions regarding inter subject synchronisation.

A second line of future work concerns the extension of the experimental paradigms to populations and contexts beyond those considered in this dissertation. The lexical and speech related tasks presented in chapter 3, for example, could be applied to individuals with specific learning disorders, developmental language impairments or neurodegenerative conditions, in order to assess whether the multimodal signatures observed in healthy

young adults generalise or undergo systematic transformations. Similarly, the game based paradigms developed in chapter 4 provide a flexible platform for investigating engagement, attentional control and cognitive efficiency in populations with mild cognitive impairment, dementia, attention related disorders or mood disturbances. In these primarily individual task settings, the combined analysis of EEG, autonomic measures including HRV and EDA, pupillometry and behavioural performance may yield sensitive markers of fatigue, disengagement and emotional dysregulation.

The dyadic paradigms introduced in chapter 5, based on EDA hyperscanning and EEG hyperscanning with cross biofeedback, could be extended to pairs characterised by different relational structures, such as parent child dyads, patient caregiver pairs or therapeutic dyads. These extensions would allow for a systematic investigation of how interpersonal synchrony relates to attachment patterns, communicative style and therapeutic alliance, and how such synchrony is modulated by individual traits and asymmetries within the dyad. While the present work focused on neural and electrodermal coupling in these contexts, future studies could explore how additional autonomic or behavioural channels might contribute to a more comprehensive characterisation of interpersonal dynamics.

A third set of future directions concerns the ecological validity and complexity of stimuli and tasks. Although this thesis has already moved beyond classical trial based paradigms by incorporating interactive serious games and shared affective viewing, future research could further increase ecological richness by employing immersive environments such as virtual reality or naturalistic stimuli unfolding over extended timescales. Within such contexts, multimodal physiological recording could be used to examine how individuals and dyads navigate complex, temporally structured scenarios that more closely resemble real life experiences, including social decision making, joint action or emotionally charged interpersonal encounters. Of particular interest would be the implementation of adaptive mechanisms that modify task demands or feedback based on online estimates of engagement, arousal or synchronisation. In this sense, the biofeedback and cross biofeedback paradigms explored in the present work can be viewed as preliminary steps toward closed loop experimental systems, which would enable direct testing of causal hypotheses about how modulating information channels influences both intra and inter subject dynamics.

From a translational perspective, the multimodal markers identified in

this thesis suggest several potential applications. In education and training, indices of engagement derived from EEG, autonomic measures, pupillometry and behavioural performance could be incorporated into serious games or learning platforms that adapt difficulty and feedback in real time, maintaining an optimal balance between challenge and skill. In clinical contexts, similar indices could inform monitoring tools aimed at detecting early signs of cognitive overload, emotional dysregulation or disengagement during rehabilitation or cognitive training, thereby supporting personalised intervention strategies. The dyadic and hyperscanning frameworks may also inspire interventions targeting social cognition, for instance by using biofeedback to enhance awareness of interpersonal synchrony or by designing therapeutic protocols that manipulate shared emotional stimulation to foster empathic engagement. In human machine interaction, multimodal physiological monitoring could support the development of adaptive interfaces responsive to users' cognitive and affective states, representing a broader generalisation of the principles tested in the experimental paradigms of this thesis.

At a conceptual level, future work could further embed the empirical findings of this dissertation within broader theoretical frameworks, such as predictive processing accounts of perception and action or contemporary models of social cognition. The multidisciplinary approach adopted here allows for an integrated examination of central, autonomic and behavioural processes across multiple levels of complexity. The sensitivity to authenticity and semantic structure observed in chapter 3, the dynamic regulation of engagement in ecologically oriented tasks in chapter 4, and the trait dependent patterns of interpersonal synchronisation reported in chapter 5 can be interpreted as complementary expressions of adaptive predictive mechanisms that continuously adjust internal models to reduce uncertainty and maintain coherence between expectations and sensory input, both at the individual and interpersonal level. Systematically formalising these interpretations, for example by linking physiological markers to computational quantities such as prediction error or precision, would strengthen the theoretical grounding of multimodal psychophysiology and facilitate dialogue with adjacent fields, including computational psychiatry and social neuroscience.

In summary, the directions outlined above indicate that the contributions of this thesis are not limited to the specific paradigms and samples investigated. Rather, they provide the basis for a coherent and extensible research programme in which multimodal, dynamic and socially informed approaches

to psychophysiology are progressively refined, integrated and applied. By expanding the methodological repertoire, broadening the range of populations and contexts, and deepening theoretical integration, future work can build on the present findings to advance both fundamental understanding and applied solutions in the study of human cognition, emotion and social interaction.

Appendix A

Appendix

A.1 Supplementary Materials of chapter 3

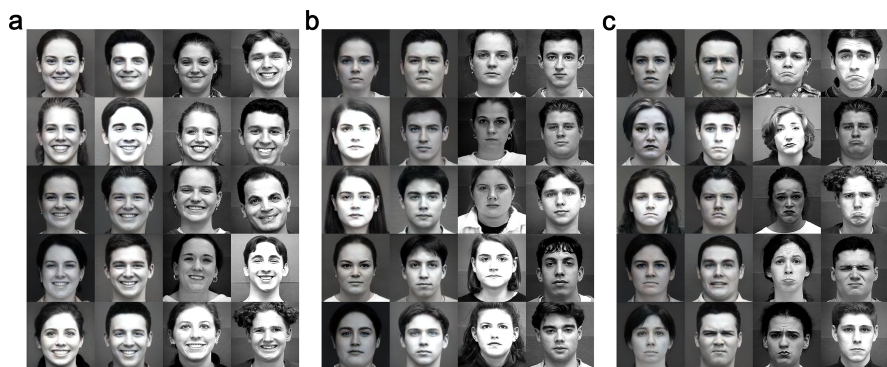


Figure A.1: All 60 images of human faces used in the proposed visual stimuli task. (a) Happy set, (b) Neutral set, (c) Sad set. For each set, the leftmost column report real faces of woman, then faces of real men, AI-generated faces of woman and, finally, AI-generated faces of men.

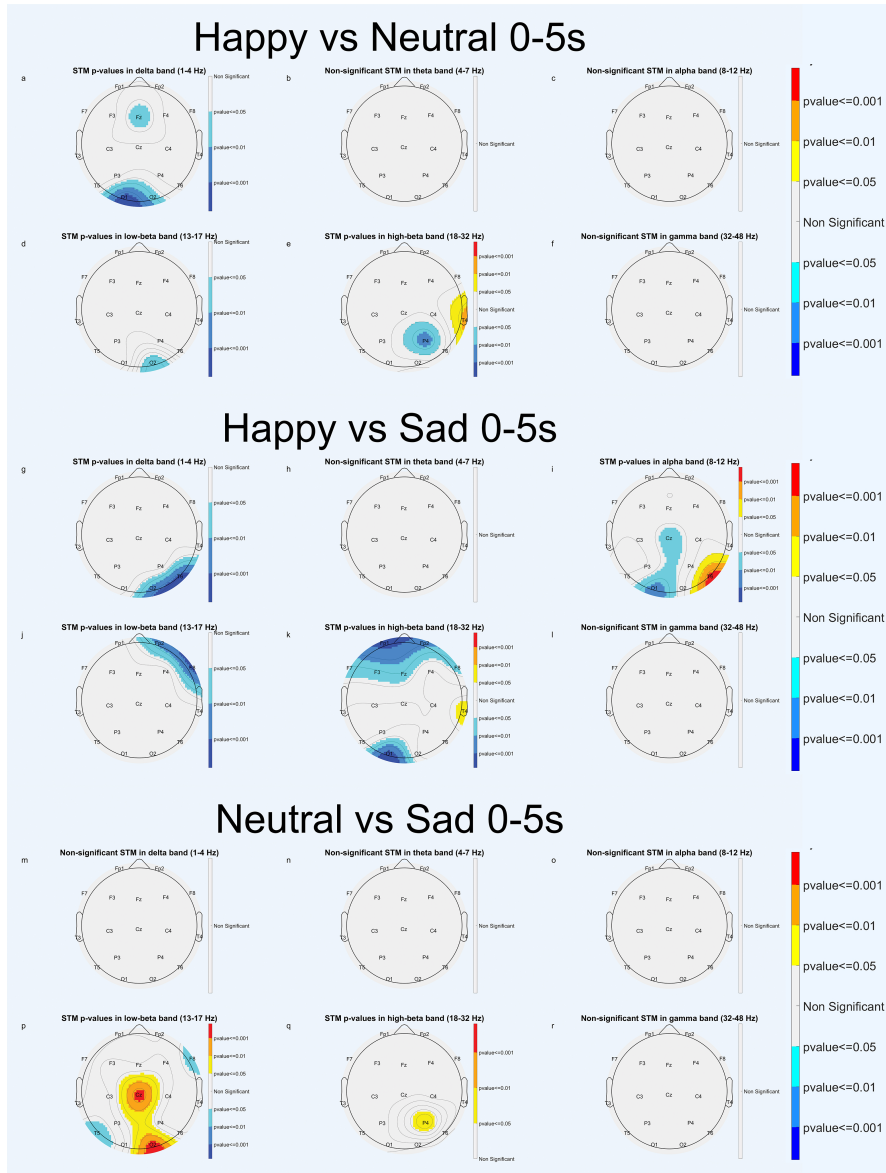


Figure A.2: STMs of significant statistical activation of brain areas in Emotional comparisons (0–5 s). "Happy vs. Neutral" comparison (a–f); (a) delta band, (b) theta band, (c) alpha band, (d) low-beta band, (e) high-beta band, (f) gamma band. "Happy vs. Sad" comparison (g–l); (g) delta band, (h) theta band, (i) alpha band, (j) low-beta band, (k) high-beta band, (l) gamma band. "Neutral vs. Sad" comparison (m–r); (m) delta band, (n) theta band, (o) alpha band, (p) low-beta band, (q) high-beta band, (r) gamma band (see section 3.1).

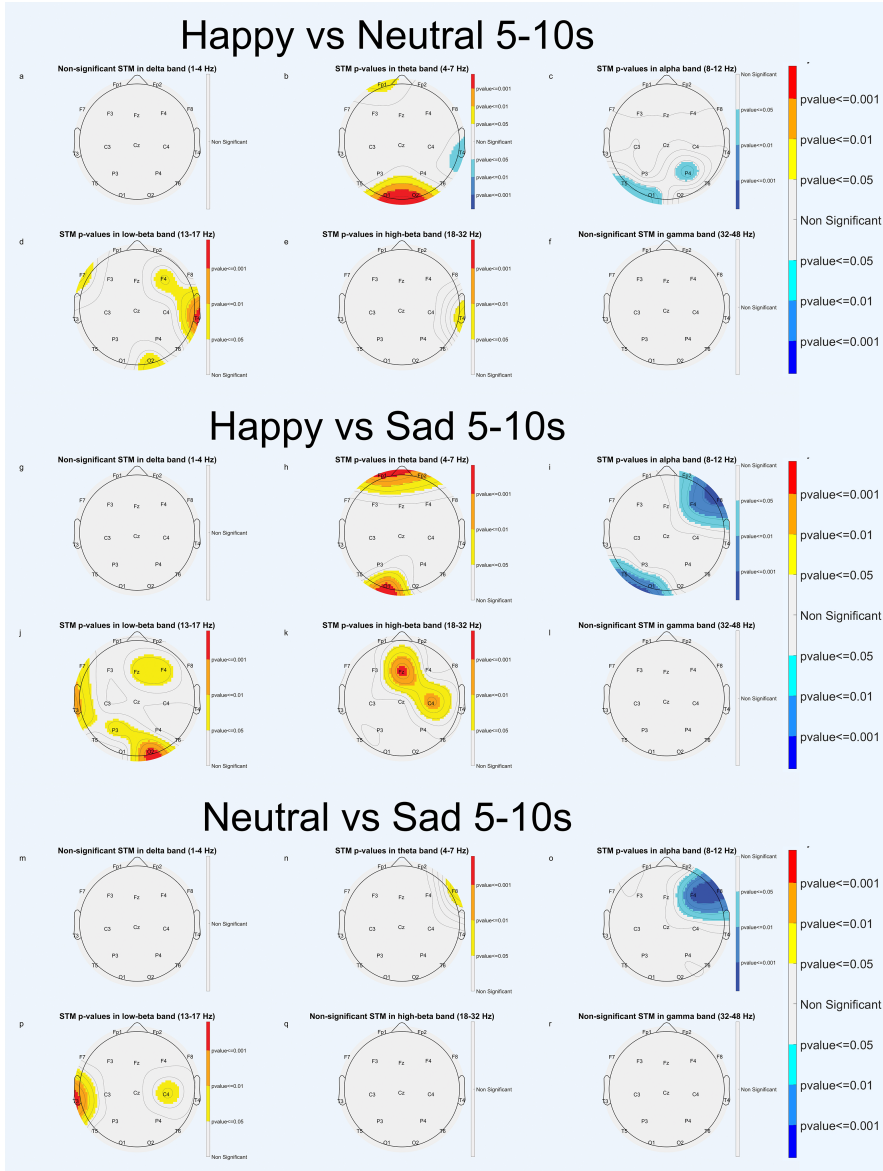


Figure A.3: STMs of significant statistical activation of brain areas in Emotional comparisons (5–10 s). "Happy vs. Neutral" comparison (a–f); (a) delta band, (b) theta band, (c) alpha band, (d) low-beta band, (e) high-beta band, (f) gamma band. "Happy vs. Sad" comparison (g–l); (g) delta band, (h) theta band, (i) alpha band, (j) low-beta band, (k) high-beta band, (l) gamma band. "Neutral vs. Sad" comparison (m–r); (m) delta band, (n) theta band, (o) alpha band, (p) low-beta band, (q) high-beta band, (r) gamma band (see section 3.1).

A.2 Supplementary Materials of chapter 4

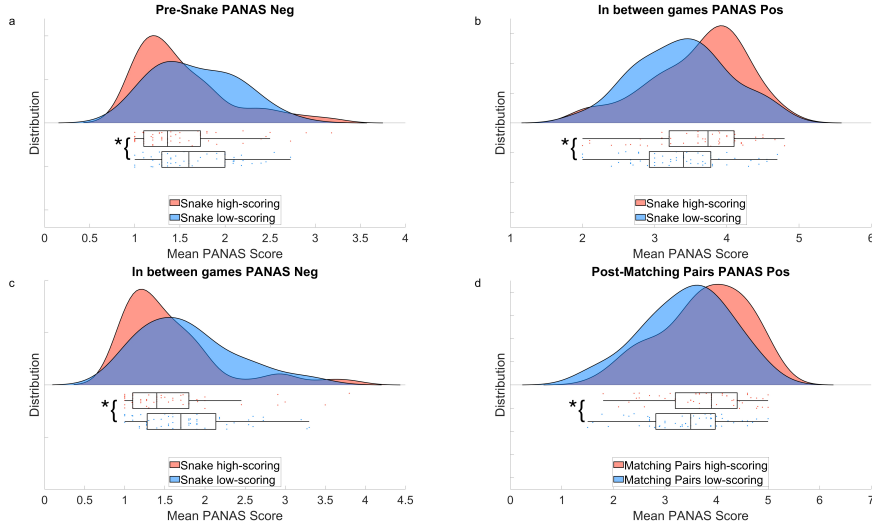


Figure A.4: Significant comparisons resulting from PANAS scores analysis before and after the Snake and the Matching Pairs games. *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$ (see section 4.4).

Category	Feature	Description
WAFFER Features	WAFEREn	Unpredictability of transitions in the MC of FE emotions.
	WAFERSt	Tendency of the system to remain in the same state over time.
	WAFERSpG	Speed at which the MC converges to its steady-state distribution.
	meanAngry	Mean of 'Angry' FE during the games.
	meanDisgust	Mean of 'Disgust' FE during the games.
	meanFear	Mean of 'Fear' FE during the games.
	meanHappy	Mean of 'Happy' FE during the games.
	meanNeutral	Mean of 'Neutral' FE during the games.
	meanSad	Mean of 'Sad' FE during the games.
	meanSurprise	Mean of 'Surprise' FE during the games.
HRV 'canonical' Features	meanRR	Average heart rate interval between successive R-peaks.
	stdRR	Standard deviation of NN intervals.
	RMSSD	Root mean square of successive differences between NN intervals.
	NN50 RR	Count of successive NN interval pairs differing by more than 50 ms.
	pNN50	Proportion of NN50 relative to total NN intervals.
	TriRR	Triangular index calculated as sum of histogram values divided by its peak.
	TINN	Baseline width of RR interval histogram based on 20 bins.
	meanDER1	Mean of the first derivative of RR intervals.
	stdDER1	Standard deviation of the first derivative of RR intervals.
	meanDER2	Mean of the second derivative of RR intervals.
	stdDER2	Standard deviation of the second derivative of RR intervals.
	WelchVLFpow	Spectral power in very-low-frequency range (0–0.04 Hz).
	WelchLFpow	Spectral power in low-frequency range (0.04–0.15 Hz).
	WelchHFpow	Spectral power in high-frequency range (0.15–0.4 Hz).
	WelchVLFpeak	Peak spectral value in the very-low-frequency range.
	WelchLFpeak	Peak spectral value in the low-frequency range.
	WelchHFpeak	Peak spectral value in the high-frequency range.
	ApEn	Approximate entropy, a measure of signal complexity and irregularity.
	SampEn1	Sample entropy of RR intervals ($m = 2$, $r = 0.2$).
	SampEn2	Sample entropy of RR intervals ($m = 3$, $r = 0.2$).
	SampEn3	Sample entropy of RR intervals ($m = 4$, $r = 0.2$).
	SampEn4	Sample entropy of RR intervals ($m = 5$, $r = 0.2$).
	DistEn	Distribution Entropy of RR intervals ($m = 5$, $\tau = 3$).
HRV 'complex' Features	FractDimRR	Fractal dimension of RR intervals.
	DFARR	Detrended fluctuation analysis of RR intervals.
	recurrence rate (RR)	Proportion of recurrent points in a recurrence plot.
	determinism	Measure of predictability in recurrence analysis.
	average diagonal length	Mean diagonal line length in recurrence plot.
	entropy	Entropy of diagonal line lengths in recurrence plot.
	mean recurrence time (RT)	Mean time between recurrent states.
	max recurrence plot (RP) path length	Longest diagonal path in recurrence plot.
	laminarity	Proportion of laminar states in recurrence analysis.
	trapping time (TT)	Average duration of laminar states in recurrence analysis.

Table A.1: Features considered in GLMM analysis for Step II (see section 4.4).

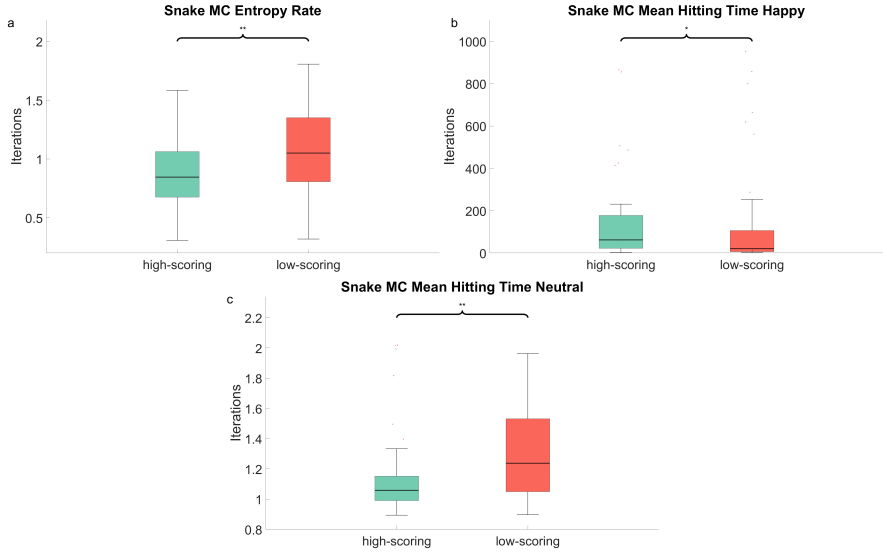


Figure A.5: Boxplots of significant comparisons between high scoring and low scoring players in the Snake game. *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$ (see section 4.4).

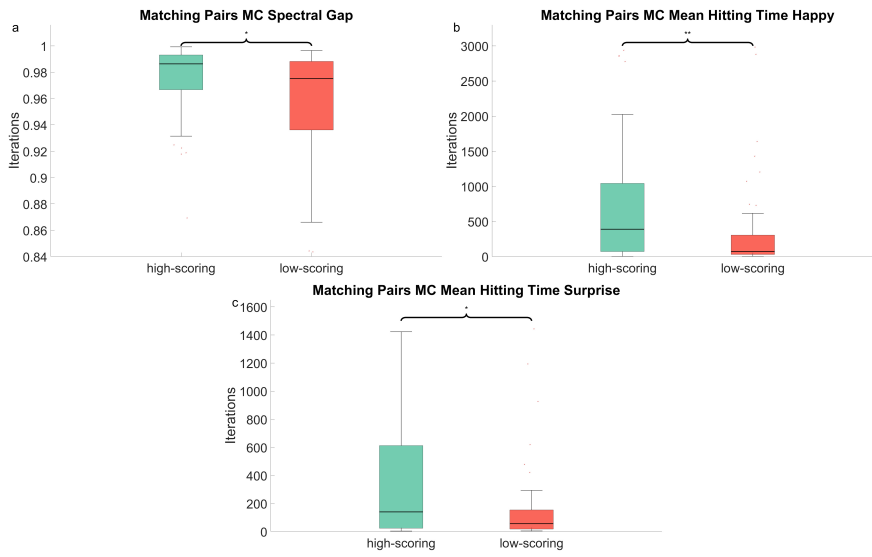


Figure A.6: Boxplots of significant comparisons between high scoring and low scoring players in the Matching Pairs game. *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$ (see section 4.4).

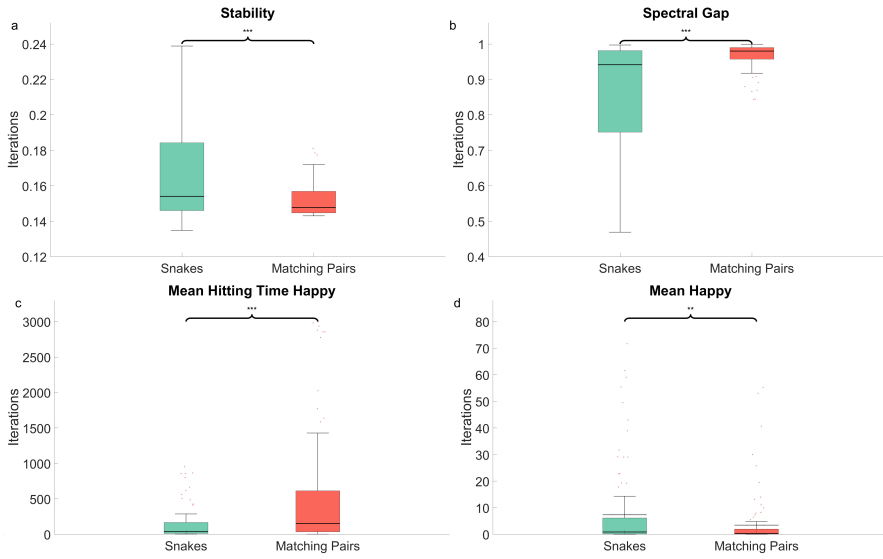


Figure A.7: Boxplots of significant comparisons of MC-related features in the Snake and Matching Pairs games. *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$ (see section 4.4).

Appendix B

Publications

This research activity has led to several publications in international journals and conferences. These are summarized below.¹

International Journals

1. **Tarchi P.**, Lanini M. C., Frassinetti L., & Lanatà A. “Real and deepfake face recognition: An EEG study on cognitive and emotive implications.” *Brain Sciences*, 2023. [DOI:10.3390/brainsci13091233]
2. Gursesli M.C., Chen S., Dewantoro M.F., You X., Anbar E., Taveekitworachai P., Abdullah F., **Tarchi P.**, Duradoni M., & Lanatà A, Guazzini A., Thawonmas R. “The Role of Large Language Model-Generated Stories in the Narrative Experience of Serious Visual Novel Games” *International Journal of Human-Computer Interaction*, 2025. [DOI:10.1080/10447318.2025.2528993]
3. Gursesli M. C. and **Tarchi P.**, Calà F., Frassinetti L., Guazzini A., Duradoni M., Park K., Thawonmas R., You X., Lanatà A. “Multimodal Analysis of Emotions in Gaming: Understanding Cultural Influences”, *IEEE Transactions on Affective Computing*, 2026. [DOI:10.1109/taffc.2026.3660362]

Submitted

1. **Tarchi P.**, Frassinetti L., Bigagli L., Pitterà V., Lanatà A. “Temporal Dynamics of Functional Connectivity during Neuroaesthetic Experience: Effects of Art Expertise and Psychological Traits”, *BIOSIGNALS 2026*. (Accepted for Presentation)

¹The author’s bibliometric indices are the following: *H*-index = 3, total number of citations = 36 (source: Google Scholar on March, 2026).

2. **Tarchi P.**, Gursesli M.C., Galeote D.F., Hamari J., Baroni M., Marzi T., Khan I., Thawonmas R., Lanatà A. “Brain in the Game: EEG Markers and Affective Evaluation of Engagement and Performance in a Casual Game”, *CHI PLAY 2026*. (Submitted)

International Conferences and Workshops

1. **Tarchi P.**, Calà F., Frassinetti L., Lanatà A. “Electroencephalographic Correlates in Synthetic and Real Emotional Face Stimulation”, in *Proc. of 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Sydney (Australia), 2023.
2. Calà F., **Tarchi P.**, Frassinetti L., Gursesli M. C., Guazzini A., Lanatà A. “Eye-tracking correlates of the Implicit Association Test”, in *Proc. of 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Sydney (Australia), 2023.
3. Gursesli M. C., Calà F., **Tarchi P.**, Frassinetti L., , Guazzini A., Lanatà A. “Eyetracking correlated in the matching pairs game”, in *Proc. of 2023 IEEE Gaming, Entertainment, and Media Conference (GEM)*, Bridgetown, (Barbados), 2023.
4. Calà F., Frassinetti L., **Tarchi P.**, Guarguagli V., Manfredi C., Lanatà A. “Electrodermal activity and acoustical analysis in a words/non-words reading task”, in *Proc. of Models and Analysis of Vocal Emissions for Biomedical Applications (MAVEBA) National Conference*, Florence, Italy, 2023.
5. Calà F., **Tarchi P.**, Frassinetti L., Gursesli M. C., Guazzini A., Lanatà A. “Expectancy Violation: Climate Change Associations May Reveal Underlying Brain-Evoked Responses of Implicit Attitudes”, in *Proc. of 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Orlando (USA), 2024.
6. **Tarchi P.**, Calà F., Frassinetti L., Lanatà A. “Event-Related Potentials in Complex and Simple Words-Pseudowords Aloud Reading Task”, in *Proc. of 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Orlando (USA), 2024.
7. Gursesli M. C., Calà F., **Tarchi P.**, Frassinetti L., Guazzini A., Duradoni M., Thawonmas R., Lanatà A. “Understanding Game Performance: A Study of Eye Blinking and Pupil Metrics in Matching Pairs Game”, in *Proc. of 2024 IEEE Conference on Games (CoG)*, Milan (Italy), 2024.
8. **Tarchi P.**, Calà F., Frassinetti L., Lanatà A. “Event-Related Potentials in Complex and Simple Words-Pseudowords Aloud Reading Task”, in *Proc. of 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Orlando (USA), 2024.

9. Calà F., Gursesli M. C., **Tarchi P.**, Frassinetti L., Guazzini A., Lanatà A. “Pupil Dilation Dynamics in Serious Game Emotional Activation”, in *Proc. of IEEE Gaming, Entertainment, and Media Conference (GEM)*, Turin, (Italy), 2024.
10. **Tarchi P.**, Gursesli M. C., Calà F., Frassinetti L., Guazzini A., Lanatà A. “Markov Chain Modeling of Facial Emotions’ Dynamics in Video Games”, in *Proc. of IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0 & IoT)*, Florence, Italy, 2024.
11. **Tarchi P.**, Frassinetti L., Faralli G., Calà F., Lanini M.C., Lanatà A. “Quantitative Electrodermal Activity Analysis of Simultaneous Recordings from Dyads during Affective Visual Task: Proof of Concept and Preliminary Results”, in *Proc. of 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Copenhagen (Denmark), 2025.
12. Calà F., Frassinetti L., **Tarchi P.**, Cantarella G., Buccichini G., Battilocchi L., Lanatà A. “Acoustic and Sentiment Analyses for Voice and Life Quality Characterisation After Medical Intervention in Voice Pathologies”, in *Proc. of 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Copenhagen (Denmark), 2025.
13. Frassinetti L., Guarguagli V., Petraccone C., **Tarchi P.**, Calà F., Lanini M.C., Marzi T., Lanatà A. “Integrating Intersubject Biofeedback in Hyperscanning visual affective experiment: proof of concept and preliminary results on HRV dynamics”, in *Proc. of 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Copenhagen (Denmark), 2025.
14. Gursesli M.C., **Tarchi P.**, Guazzini A., Duradoni M., Yaras A.T., Akinci E., Yurdakul U., Calà F., Tonacci A., Vilone D., Lanatà A. “Silent vs. Sound: The Impact of Uniform Auditory Stimuli on Eye Movements and Game Performance”, in *Proc. of 2025 IEEE Gaming, Entertainment, and Media Conference (GEM)*, Kaohsiung (Taiwan), 2025.

Book Chapters

1. Frassinetti L., **Tarchi P.**, Calà F., Lanatà A. - In: Mainardi L., Scilingo E.P., Astolfi L. (curated by). “Unlocking the mind and emotions: cutting-edge bioengineering techniques from computational physiology to clinical applications”, Pàtron Editore, 2025. (Chapter 7 – Wearable technologies for emotion monitoring: measuring physiological and behavioral signals).

Bibliography

- [1] “”unlimited free face mix ai generator - playform - ai art generative platform for artists and creative people. free, unlimited, easy.” playform. [online],” <https://playform.io/facemix>, accessed: 01-Feb-2023.
- [2] D. Acunzo, G. MacKenzie, and M. C. van Rossum, “Spatial attention affects the early processing of neutral versus fearful faces when they are task-irrelevant: a classifier study of the eeg c1 component,” *Cognitive, Affective, & Behavioral Neuroscience*, vol. 19, pp. 123–137, 2019.
- [3] R. Adolphs, “Neural systems for recognizing emotion,” *Current opinion in neurobiology*, vol. 12, no. 2, pp. 169–177, 2002.
- [4] —, “Recognizing emotion from facial expressions: psychological and neurological mechanisms,” *Behavioral and cognitive neuroscience reviews*, vol. 1, no. 1, pp. 21–62, 2002.
- [5] Y. Ahmed, A. Singh, and Y. Zhao, “Eeg-based engagement monitoring in cognitive games,” *Sensors*, vol. 25, no. 7, p. 2072, 2025.
- [6] L. Ahonen, B. U. Cowley, A. Hellas, and K. Puolamäki, “Biosignals reflect pair-dynamics in collaborative work: Eda and ecg study of pair-programming in a classroom environment,” *Scientific reports*, vol. 8, no. 1, p. 3138, 2018.
- [7] N. Ahufinger, A. Berglund-Barraza, A. Cruz-Santos, L. Ferinu, L. Andreu, M. Sanz-Torrent, and J. L. Evans, “Consistency of a nonword repetition task to discriminate children with and without developmental language disorder in catalan–spanish and european portuguese speaking children,” *Children*, vol. 8, no. 2, p. 85, 2021.
- [8] M. Akhand, S. Roy, N. Siddique, M. A. S. Kamal, and T. Shimamura, “Facial emotion recognition using transfer learning in the deep cnn,” *Electronics*, vol. 10, no. 9, p. 1036, 2021.
- [9] P. Albiero, S. Ingoglia, A. Lo Coco *et al.*, “Contributo all’adattamento italiano dell’interpersonal reactivity index,” *Testing Psicometria Metodologia*, vol. 13, no. 2, pp. 107–125, 2006.

- [10] N. Ali, S. Tajuddin, and A. Bramantoro, "Emotions in video games: An investigation of game mechanic influences," in *2023 6th International Conference on Applied Computational Intelligence in Information Systems (ACIIS)*. IEEE, 2023, pp. 1–6.
- [11] R. A. Allegretta, K. Rovelli, and M. Balconi, "The role of emotion regulation and awareness in psychosocial stress: an eeg-psychometric correlational study," in *Healthcare*, vol. 12, no. 15. MDPI, 2024, p. 1491.
- [12] A. Althubaiti, "Information bias in health research: definition, pitfalls, and adjustment methods," *Journal of multidisciplinary healthcare*, pp. 211–217, 2016.
- [13] O. AlZoubi, B. AlMakhadmeh, M. Bani Yassein, and W. Mardini, "Detecting naturalistic expression of emotions using physiological signals while playing video games," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 2, pp. 1133–1146, 2023.
- [14] G. Anmella, A. Mas, M. Sanabra, C. Valenzuela-Pascual, M. Valentí, I. Pachiarotti, A. Benabarre, I. Grande, M. De Prisco, V. Oliva *et al.*, "Electrodermal activity in bipolar disorder: Differences between mood episodes and clinical remission using a wearable device in a real-world clinical setting," *Journal of Affective Disorders*, vol. 345, pp. 43–50, 2024.
- [15] P. Antonenko, F. Paas, R. Grabner, and T. Van Gog, "Using electroencephalography to measure cognitive load," *Educational psychology review*, vol. 22, no. 4, pp. 425–438, 2010.
- [16] B. M. Appelhans and L. J. Luecken, "Heart rate variability as an index of regulated emotional responding," *Review of general psychology*, vol. 10, no. 3, pp. 229–240, 2006.
- [17] X. Arakaki, R. J. Arechavala, E. H. Choy, J. Bautista, B. Bliss, C. Molloy, D.-A. Wu, S. Shimojo, Y. Jiang, M. T. Kleinman *et al.*, "The connection between heart rate variability (hrv), neurological health, and cognition: A literature review," *Frontiers in neuroscience*, vol. 17, p. 1055445, 2023.
- [18] Arduino, "Arduino mkr wifi 1010," 2025, accessed: 2025-01-08. [Online]. Available: <https://store.arduino.cc/products/arduino-mkr-wifi-1010>
- [19] Arushi, R. Dillon, and A. N. Teoh, "Real-time stress detection model and voice analysis: An integrated vr-based game for training public speaking skills," in *2021 IEEE Conference on Games (CoG)*, 2021, pp. 1–4.
- [20] V. Ashley, P. Vuilleumier, and D. Swick, "Time course and specificity of event-related potentials to emotional expressions," *Neuroreport*, vol. 15, no. 1, pp. 211–216, 2004.

- [21] R. Averill, "Depression of thyrotropin releasing factor induction of thyrotropin release by thyroxine in small doses," *Endocrinology*, vol. 85, no. 1, pp. 67–71, 1969.
- [22] S. Aydore, D. Pantazis, and R. M. Leahy, "A note on the phase locking value and its properties," *Neuroimage*, vol. 74, pp. 231–244, 2013.
- [23] H. Azzam, M. Mansour, and D. Khalil, "Video game playing effects on young adults' brain rhythm: qeeg study," *Discover Sensors*, vol. 3, p. 100129, 2025.
- [24] F. Babiloni, F. Cincotti, D. Mattia, M. Mattiocco, F. D. V. Fallani, A. Tocci, L. Bianchi, M. G. Marciani, and L. Astolfi, "Hypermethods for eeg hyper-scanning," in *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2006, pp. 3666–3669.
- [25] M. Babo-Rebelo, A. Puce, D. Bullock, L. Hugueville, F. Pestilli, C. Adam, K. Lehongre, V. Lambrecq, V. Dinkelacker, and N. George, "Visual information routes in the posterior dorsal and ventral face network studied with intracranial neurophysiology and white matter tract endpoints," *Cerebral Cortex*, vol. 32, no. 2, pp. 342–366, 2022.
- [26] M. Balconi, R. A. Allegretta, and L. Angioletti, "Autonomic synchrony induced by hyperscanning interoception during interpersonal synchronization tasks," *Frontiers in Human Neuroscience*, vol. 17, p. 1200750, 2023.
- [27] M. Balconi *et al.*, "Brain plasticity and rehabilitation by using near-infrared spectroscopy," *Neuropsychological Trends*, vol. 19, no. 19, pp. 71–82, 2016.
- [28] M. Balconi and M. E. M. E. Vanutelli, "Empathy in negative and positive interpersonal interactions. what is the relationship between central (eeg, fnirs) and peripheral (autonomic) neurophysiological responses?" *Advances in cognitive psychology*, vol. 13, no. 1, p. 105, 2017.
- [29] A. Baldini, S. Frumento, D. Menicucci, A. Gemignani, E. P. Scilingo, and A. Greco, "Subjective fear in virtual reality: a linear mixed-effects analysis of skin conductance," *IEEE Transactions on Affective Computing*, vol. 13, no. 4, pp. 2047–2057, 2022.
- [30] R. Barbieri, E. C. Matten, A. A. Alabi, and E. N. Brown, "A point-process model of human heartbeat intervals: new definitions of heart rate and heart rate variability," *American Journal of Physiology-Heart and Circulatory Physiology*, vol. 288, no. 1, pp. H424–H435, 2005.
- [31] P. Bard, "A diencephalic mechanism for the expression of rage with special reference to the sympathetic nervous system," *American Journal of Physiology-Legacy Content*, vol. 84, no. 3, pp. 490–515, 1928.
- [32] P. Barraza, A. Pérez, and E. Rodríguez, "Brain-to-brain coupling in the gamma-band as a marker of shared intentionality," *Frontiers in Human Neuroscience*, vol. 14, p. 295, 2020.

- [33] L. F. Barrett, "Valence is a basic building block of emotional life," *Journal of Research in Personality*, vol. 40, no. 1, pp. 35–55, 2006.
- [34] —, "The theory of constructed emotion: an active inference account of interoception and categorization," *Social cognitive and affective neuroscience*, vol. 12, no. 1, pp. 1–23, 2017.
- [35] L. F. Barrett, R. Adolphs, S. Marsella, A. M. Martinez, and S. D. Pollak, "Emotional expressions reconsidered: Challenges to inferring emotion from human facial movements," *Psychological science in the public interest*, vol. 20, no. 1, pp. 1–68, 2019.
- [36] J. J. Barton, "Face processing in the temporal lobe," in *Handbook of Clinical Neurology*. Elsevier, 2022, vol. 187, pp. 191–210.
- [37] E. Başar, C. Başar-Eroğlu, S. Karakaş, and M. Schürmann, "Brain oscillations in perception and memory," *International journal of psychophysiology*, vol. 35, no. 2-3, pp. 95–124, 2000.
- [38] A. M. Bastos and J.-M. Schoffelen, "A tutorial review of functional connectivity analysis methods and their interpretational pitfalls," *Frontiers in systems neuroscience*, vol. 9, p. 175, 2016.
- [39] A. Battisti, G. Lazzaro, F. Costanzo, C. Varuzza, S. Rossi, S. Vicari, and D. Menghini, "Effects of a short and intensive transcranial direct current stimulation treatment in children and adolescents with developmental dyslexia: A crossover clinical trial," *Frontiers in Psychology*, vol. 13, p. 986242, 2022.
- [40] M. Bauer, M.-P. Stenner, K. J. Friston, and R. J. Dolan, "Attentional modulation of alpha/beta and gamma oscillations reflect functionally distinct processes," *Journal of Neuroscience*, vol. 34, no. 48, pp. 16 117–16 125, 2014.
- [41] N. Bea, "“neuroscience as a new opportunity for museums”,” Mar. 2020, musei-it, 31 March 2020. [Online]. Available: <https://www.musei-it.com/post/le-neuroscienze-come-nuova-opportunit%C3%A0-per-i-musei>
- [42] M. Behnke, J. J. Gross, and L. D. Kaczmarek, "The role of emotions in esports performance." *Emotion*, vol. 22, no. 5, p. 1059, 2022.
- [43] C. Berka, D. J. Levendowski, M. N. Lumicao, A. Yau, G. Davis, V. Zivkovic, R. Olmstead, P. D. Tremoulet, and P. L. Craven, "Eeg correlates of task engagement and mental workload in vigilance, learning, and memory tasks," *Aviation, Space, and Environmental Medicine*, vol. 78, no. 5, pp. B231–B244, 2007.
- [44] R. Berta, F. Bellotti, A. De Gloria, D. Pranantha, and C. Schatten, "Electroencephalogram and physiological signal analysis for assessing flow in games," *IEEE Transactions on Computational Intelligence and AI in Games*, vol. 5, no. 2, pp. 164–175, 2013.

- [45] A. Betella, R. Zucca, R. Cetnarski, A. Greco, A. Lanatà, D. Mazzei, A. Tognetti, X. D. Arsiwalla, P. Omedas, D. De Rossi *et al.*, “Inference of human affective states from psychophysiological measurements extracted under ecologically valid conditions,” *Frontiers in neuroscience*, vol. 8, p. 286, 2014.
- [46] N. Bigdely-Shamlo, T. Mullen, C. Kothe, K.-M. Su, and K. A. Robbins, “The prep pipeline: standardized preprocessing for large-scale eeg analysis,” *Frontiers in neuroinformatics*, vol. 9, p. 16, 2015.
- [47] M. Bilal, S. Razzaq, N. Bhowmike, A. Farooq, M. Zahid, and S. Shoaib, “Facial recognition using hidden markov model and convolutional neural network,” *AI*, vol. 5, no. 3, pp. 1633–1647, 2024.
- [48] P. Binda and S. O. Murray, “Spatial attention increases the pupillary response to light changes,” *Journal of vision*, vol. 15, no. 2, pp. 1–1, 2015.
- [49] P. M. Blom, S. Bakkes, and P. Spronck, “Modeling and adjusting in-game difficulty based on facial expression analysis,” *Entertainment Computing*, vol. 31, p. 100307, 2019.
- [50] P. M. Blom, S. Bakkes, C. Tan, S. Whiteson, D. Roijers, R. Valenti, and T. Gevers, “Towards personalised gaming via facial expression recognition,” in *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, no. 1, 2014, pp. 30–36.
- [51] A. Boffet, L. M. Arsac, V. Ibanez, F. Sauvet, and V. Deschodt-Arsac, “Detection of cognitive load modulation by eda and hrv,” *Sensors*, vol. 25, no. 8, p. 2343, 2025.
- [52] J. Bowlby, “Attachment and loss. vol. 1, attachment. new york: Basic, 1982,” *Attachment and loss*, vol. 2, 1969.
- [53] C. H. Bowman and O. H. Turnbull, “Emotion-based learning on a simplified card game: The iowa and bangor gambling tasks,” *Brain and Cognition*, vol. 55, no. 2, pp. 277–282, 2004.
- [54] M. M. Bradley and P. J. Lang, “Measuring emotion: the self-assessment manikin and the semantic differential,” *Journal of behavior therapy and experimental psychiatry*, vol. 25, no. 1, pp. 49–59, 1994.
- [55] M. M. Bradley, L. Miccoli, M. A. Escrig, and P. J. Lang, “The pupil as a measure of emotional arousal and autonomic activation,” *Psychophysiology*, vol. 45, no. 4, pp. 602–607, 2008.
- [56] N. Brady, M. Campbell, and M. Flaherty, “Perceptual asymmetries are preserved in memory for highly familiar faces of self and friend,” *Brain and cognition*, vol. 58, no. 3, pp. 334–342, 2005.

- [57] D. Branco, O. F. Goncalves, and S. B. i. Badia, "A systematic review of international affective picture system (iaps) around the world," *Sensors*, vol. 23, no. 8, p. 3866, 2023.
- [58] N. M. Brashier and E. J. Marsh, "Judging truth," *Annual review of psychology*, vol. 71, pp. 499–515, 2020.
- [59] I. Brinck, "Empathy, engagement, entrainment: The interaction dynamics of aesthetic experience," *Cognitive processing*, vol. 19, no. 2, pp. 201–213, 2018.
- [60] J. H. Brockmyer, C. M. Fox, K. A. Curtiss, E. McBroom, K. M. Burkhart, and J. N. Pidruzny, "The development of the game engagement questionnaire: A measure of engagement in video game-playing," *J Exp Soc Psychol*, vol. 45, no. 4, pp. 624–634, 2009.
- [61] V. Bruce and A. Young, "Understanding face recognition," *British journal of psychology*, vol. 77, no. 3, pp. 305–327, 1986.
- [62] A. Buss, "The evolution of western individualism," *Religion*, vol. 30, no. 1, pp. 1–25, 2000.
- [63] J. T. Cacioppo, L. G. Tassinary, and G. Berntson, *Handbook of psychophysiology*. Cambridge university press, 2007.
- [64] F. Calà, L. Frassinetti, P. Tarchi, V. Guarguagli, C. Manfredi, and A. Lanatà, "Electrodermal activity and acoustical analysis in a words/non-words reading task," pp. 99–102, 2023.
- [65] F. Calà, M. C. Gursesli, P. Tarchi, L. Frassinetti, A. Guazzini, and A. Lanata, "Pupil dilation dynamics in serious game emotional activation," in *2024 IEEE Gaming, Entertainment, and Media Conference (GEM)*. IEEE, 2024, pp. 1–4.
- [66] N. Campbell, "Sources of competitive rivalry in japan," *Journal of Product Innovation Management*, vol. 2, no. 4, pp. 224–231, 1985.
- [67] A. Canales-Johnson, R. C. Lanfranco, J. P. Morales, D. Martínez-Pernía, J. Valdés, A. Ezquerro-Nassar, Á. Rivera-Rei, A. Ibanez, S. Chennu, T. A. Bekinschtein *et al.*, "In your phase: neural phase synchronisation underlies visual imagery of faces," *Scientific Reports*, vol. 11, no. 1, p. 2401, 2021.
- [68] W. B. Cannon, "The james-lange theory of emotions: A critical examination and an alternative theory," *The American journal of psychology*, vol. 39, no. 1/4, pp. 106–124, 1927.
- [69] W. Cannon, "Neural organization for emotional expression." 1928.
- [70] D. Caruelle, A. Gustafsson, P. Shams, and L. Lervik-Olsen, "The use of electrodermal activity (eda) measurement to understand consumer emotions—a literature review and a call for action," *Journal of Business Research*, vol. 104, pp. 146–160, 2019.

- [71] V. Catrambone, L. Zallocco, E. Ramoretti, M. R. Mazzoni, L. Sebastiani, and G. Valenza, "Integrative neuro-cardiovascular dynamics in response to test anxiety: A brain-heart axis study," *Physiology & Behavior*, vol. 276, p. 114460, 2024.
- [72] W. A. Caudill, "The influence of social structure and culture on human behavior in modern japan," *The Journal of Nervous and Mental Disease*, vol. 157, no. 4, pp. 240–257, 1973.
- [73] J. F. Cavanagh and M. J. Frank, "Frontal theta as a mechanism for cognitive control," *Trends in cognitive sciences*, vol. 18, no. 8, pp. 414–421, 2014.
- [74] M. Cerezo-Pizarro, F.-I. Revuelta-Domínguez, J. Guerra-Antequera, and J. Melo-Sánchez, "The cultural impact of video games: A systematic review of the literature," *Education Sciences*, vol. 13, no. 11, p. 1116, 2023.
- [75] S. Cerutti and C. Marchesi, *Advanced methods of biomedical signal processing*. John Wiley & Sons, 2011.
- [76] S. CH and V. P, "Ameliorate grasshopper optimization algorithm based long short term memory classification for face emotion recognition system," *Multimedia Tools and Applications*, vol. 83, no. 13, pp. 37 961–37 978, 2024.
- [77] K. Chand and A. Khosla, "Efficacy of using retro games in multimodal biofeedback systems for mental relaxation," *International Journal of Gaming and Computer-Mediated Simulations (IJGCMS)*, vol. 14, no. 1, pp. 1–23, 2022.
- [78] G. Chanel, C. Rebetez, M. Bétrancourt, and T. Pun, "Emotion assessment from physiological signals for adaptation of game difficulty," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 41, no. 6, pp. 1052–1063, 2011.
- [79] C.-C. Chang and S.-T. Yang, "Interactive effects of scaffolding digital game-based learning and cognitive style on adult learners' emotion, cognitive load and learning performance," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 16, 2023.
- [80] N. Chao, W. Huang, and X. Wang, "Design of a respiratory biofeedback serious game for stress management based on hrv analysis," in *International Conference on Human-Computer Interaction*. Springer, 2023, pp. 16–24.
- [81] F. Chee, "The games we play online and offline: Making wang-tta in korea," *Popular Communication*, vol. 4, no. 3, pp. 225–239, 2006.
- [82] L. Chen, M. Li, W. Su, M. Wu, K. Hirota, and W. Pedrycz, "Adaptive feature selection-based adaboost-knn with direct optimization for dynamic emotion recognition in human–robot interaction," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 5, no. 2, pp. 205–213, 2019.

- [83] S.-M. Cheong, K. Sankaran, and H. Bastani, “Artificial intelligence for climate change adaptation,” *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 12, no. 5, p. e1459, 2022.
- [84] R. W. Cheung, C. Hartley, and P. Monaghan, “Multiple mechanisms of word learning in late-talking children: a longitudinal study,” *Journal of Speech, Language, and Hearing Research*, vol. 65, no. 8, pp. 2978–2995, 2022.
- [85] S. Chikhi, N. Matton, and S. Blanchet, “Eeg power spectral measures of cognitive workload: A meta-analysis,” *Psychophysiology*, vol. 59, no. 6, p. e14009, 2022.
- [86] K. Chowdhary, *Fundamentals of artificial intelligence*. Springer, 2020.
- [87] L. Citi, ““cvxeda.” matlab central file exchange. [online],” <https://it.mathworks.com/matlabcentral/fileexchange/53326-cvxeda>, accessed: 21-Feb-2026.
- [88] —, “cvxeda,” <https://github.com/lciti/cvxEDA>, 2025, retrieved November 24, 2025.
- [89] F. M. Citron, M. A. Gray, H. D. Critchley, B. S. Weekes, and E. C. Ferstl, “Emotional valence and arousal affect reading in an interactive way: neuroimaging evidence for an approach-withdrawal framework,” *Neuropsychologia*, vol. 56, pp. 79–89, 2014.
- [90] J. A. Coan and J. J. Allen, “Frontal eeg asymmetry as a moderator and mediator of emotion,” *Biological psychology*, vol. 67, no. 1-2, pp. 7–50, 2004.
- [91] M. X. Cohen, *Analyzing neural time series data: theory and practice*. MIT press, 2014.
- [92] A. Collins and E. Koechlin, “Reasoning, learning, and creativity: frontal lobe function and human decision-making,” *PLoS biology*, vol. 10, no. 3, p. e1001293, 2012.
- [93] T. M. Connolly, E. A. Boyle, E. MacArthur, T. Hainey, and J. M. Boyle, “A systematic literature review of empirical evidence on computer games and serious games,” *Computers & education*, vol. 59, no. 2, pp. 661–686, 2012.
- [94] F. Corallo, L. Bonanno, D. Cardile, F. Luvarà, S. Giliberto, M. Di Cara, S. Leonardi, A. Quartarone, G. Rao, and A. Pidalà, “Improvement of self-esteem in children with specific learning disorders after donkey-assisted therapy,” *Children*, vol. 10, no. 3, p. 425, 2023.
- [95] M. Costa, A. L. Goldberger, and C.-K. Peng, “Multiscale entropy analysis of complex physiologic time series,” *Physical review letters*, vol. 89, no. 6, p. 068102, 2002.
- [96] T. M. Cover, *Elements of information theory*. John Wiley & Sons, 1999.

- [97] J. R. Crawford and J. D. Henry, "The positive and negative affect schedule (panas): Construct validity, measurement properties and normative data in a large non-clinical sample," *British journal of clinical psychology*, vol. 43, no. 3, pp. 245–265, 2004.
- [98] K. Crookes, L. Ewing, J.-d. Gildenhuis, N. Kloth, W. G. Hayward, M. Oxner, S. Pond, and G. Rhodes, "How well do computer-generated faces tap face expertise?" *PloS one*, vol. 10, no. 11, p. e0141353, 2015.
- [99] X. Cui, D. M. Bryant, and A. L. Reiss, "Nirs-based hyperscanning reveals increased interpersonal coherence in superior frontal cortex during cooperation," *Neuroimage*, vol. 59, no. 3, pp. 2430–2437, 2012.
- [100] J. Cusveller, C. Gerritsen, and J. de Man, "Evoking and measuring arousal in game settings," in *Games for Training, Education, Health and Sports: 4th International Conference on Serious Games, GameDays 2014, Darmstadt, Germany, April 1-5, 2014. Proceedings 4*. Springer, 2014, pp. 165–174.
- [101] A. Czeszumski, S. Eustergerling, A. Lang, D. Menrath, M. Gerstenberger, S. Schubert, F. Schreiber, Z. Z. Rendon, and P. König, "Hyperscanning: a valid method to study neural inter-brain underpinnings of social interaction," *Frontiers in Human Neuroscience*, vol. 14, p. 39, 2020.
- [102] J. R. da Cruz, V. Chicherov, M. H. Herzog, and P. Figueiredo, "An automatic pre-processing pipeline for eeg analysis (app) based on robust statistics," *Clinical Neurophysiology*, vol. 129, no. 7, pp. 1427–1437, 2018.
- [103] M. Dabbagh and S. Shirmohammadi, "Eeg-based classification of engagement in serious games," *Computers in Human Behavior*, vol. 99, pp. 333–345, 2019.
- [104] D. Dadebayev, W. W. Goh, and E. X. Tan, "Eeg-based emotion recognition: Review of commercial eeg devices and machine learning techniques," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 7, pp. 4385–4401, 2022.
- [105] N. Dael, M. Mortillaro, and K. R. Scherer, "Emotion expression in body action and posture." *Emotion*, vol. 12, no. 5, p. 1085, 2012.
- [106] M. N. Dailey, C. Joyce, M. J. Lyons, M. Kamachi, H. Ishi, J. Gyoba, and G. W. Cottrell, "Evidence and a computational explanation of cultural differences in facial expression recognition." *Emotion*, vol. 10, no. 6, p. 874, 2010.
- [107] A. R. Damasio, "The somatic marker hypothesis and the possible functions of the prefrontal cortex," *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, vol. 351, no. 1346, pp. 1413–1420, 1996.

- [108] L. M. Daniels and M. J. Gierl, "The impact of immediate test score reporting on university students' achievement emotions in the context of computer-based multiple-choice exams," *Learning and Instruction*, vol. 52, pp. 27–35, 2017.
- [109] C. Darwin, "The expression of the emotions in man and animals. john muray, london," 1872.
- [110] R. J. Davidson, "Anterior cerebral asymmetry and the nature of emotion," *Brain and cognition*, vol. 20, no. 1, pp. 125–151, 1992.
- [111] —, "Affective style and affective disorders: Perspectives from affective neuroscience," *Cognition & emotion*, vol. 12, no. 3, pp. 307–330, 1998.
- [112] —, "Anterior electrophysiological asymmetries, emotion, and depression: Conceptual and methodological conundrums," *Psychophysiology*, vol. 35, no. 5, pp. 607–614, 1998.
- [113] R. J. Davies and O. Ikeno, *Japanese mind: Understanding contemporary Japanese culture*. Tuttle Publishing, 2011.
- [114] B. W. Davis, *The Oxford handbook of Japanese philosophy*. Oxford University Press, 2019.
- [115] M. H. Davis, "Interpersonal reactivity index," 1980.
- [116] J. B. Debruille, F. Guillem, and B. Renault, "Erps and chronometry of face recognition: following-up seeck: et al.: and george: et al." *Neuroreport*, vol. 9, no. 15, pp. 3349–3353, 1998.
- [117] J. Decety and P. L. Jackson, "The functional architecture of human empathy," *Behavioral and cognitive neuroscience reviews*, vol. 3, no. 2, pp. 71–100, 2004.
- [118] I. Deffke, T. Sander, J. Heidenreich, W. Sommer, G. Curio, L. Trahms, and A. Lueschow, "Meg/eeg sources of the 170-ms response to faces are co-localized in the fusiform gyrus," *Neuroimage*, vol. 35, no. 4, pp. 1495–1501, 2007.
- [119] A. Delorme, "Eeg is better left alone," *Scientific reports*, vol. 13, no. 1, p. 2372, 2023.
- [120] A. Delorme and S. Makeig, "Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis," *Journal of neuroscience methods*, vol. 134, no. 1, pp. 9–21, 2004.
- [121] C. Dering, C. Hemmelmann, E. Pugh, and A. Ziegler, "Statistical analysis of rare sequence variants: an overview of collapsing methods," *Genetic epidemiology*, vol. 35, no. S1, pp. S12–S17, 2011.

- [122] M. Devaux and F. Sassi, "Social disparities in hazardous alcohol use: self-report bias may lead to incorrect estimates," *The European Journal of Public Health*, vol. 26, no. 1, pp. 129–134, 2016.
- [123] S. Dikker, G. Michalareas, M. Oostrik, A. Serafimaki, H. M. Kahraman, M. E. Struiksma, and D. Poeppel, "Crowdsourcing neuroscience: inter-brain coupling during face-to-face interactions outside the laboratory," *NeuroImage*, vol. 227, p. 117436, 2021.
- [124] H. I. Dino and M. B. Abdulrazzaq, "Facial expression classification based on svm, knn and mlp classifiers," in *2019 International Conference on Advanced Science and Engineering (ICOASE)*. IEEE, 2019, pp. 70–75.
- [125] A. C. Dirican and M. Göktürk, "Psychophysiological measures of human cognitive states applied in human computer interaction," *Procedia Computer Science*, vol. 3, pp. 1361–1367, 2011.
- [126] M. Dispaldro, B. Benelli, S. Marcolini, and G. Stella, "Real-word repetition as a predictor of grammatical competence in italian children with typical language development," *International journal of language & communication disorders*, vol. 44, no. 6, pp. 941–961, 2009.
- [127] M. Dispaldro, L. B. Leonard, and P. Deevy, "Real-word and nonword repetition in italian-speaking children with specific language impairment: A study of diagnostic accuracy," 2013.
- [128] G. Donato, M. S. Bartlett, J. C. Hager, P. Ekman, and T. J. Sejnowski, "Classifying facial actions," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 21, no. 10, pp. 974–989, 1999.
- [129] C. L. Douglas, A. Tremblay, and A. J. Newman, "A two for one special: Eeg hyperscanning using a single-person eeg recording setup," *MethodsX*, vol. 10, p. 102019, 2023.
- [130] T. D. Duane and T. Behrendt, "Extrasensory electroencephalographic induction between identical twins," *Science*, vol. 150, no. 3694, pp. 367–367, 1965.
- [131] G. Dumas, J. Nadel, R. Soussignan, J. Martinerie, and L. Garnero, "Inter-brain synchronization during social interaction," *PloS one*, vol. 5, no. 8, p. e12166, 2010.
- [132] D. Dunning, C. Heath, and J. M. Suls, "Picture imperfect," *Scientific American Mind*, vol. 16, no. 4, pp. 20–27, 2005.
- [133] J. I. Durán and J.-M. Fernández-Dols, "Do emotions result in their predicted facial expressions? a meta-analysis of studies on the co-occurrence of expression and emotion." *Emotion*, vol. 21, no. 7, p. 1550, 2021.

- [134] P. Ekman, "Universals and cultural differences in facial expressions of emotion." in *Nebraska symposium on motivation*. University of Nebraska Press, 1971.
- [135] —, "An argument for basic emotions," *Cognition & emotion*, vol. 6, no. 3-4, pp. 169–200, 1992.
- [136] —, "Facial expressions," *Handbook of cognition and emotion*, vol. 16, no. 301, p. e320, 1999.
- [137] P. Ekman and W. V. Friesen, "The repertoire of nonverbal behavior: Categories, origins, usage, and coding," *semiotica*, vol. 1, no. 1, pp. 49–98, 1969.
- [138] —, "Facial action coding system," *Environmental Psychology & Nonverbal Behavior*, 1978.
- [139] P. Ekman, W. V. Friesen, M. O'sullivan, A. Chan, I. Diacoyanni-Tarlatzis, K. Heider, R. Krause, W. A. LeCompte, T. Pitcairn, P. E. Ricci-Bitti *et al.*, "Universals and cultural differences in the judgments of facial expressions of emotion." *Journal of personality and social psychology*, vol. 53, no. 4, p. 712, 1987.
- [140] P. Ekman, R. W. Levenson, and W. V. Friesen, "Autonomic nervous system activity distinguishes among emotions," *science*, vol. 221, no. 4616, pp. 1208–1210, 1983.
- [141] J. E. Else, J. Ellis, and E. Orme, "Art expertise modulates the emotional response to modern art, especially abstract: An erp investigation," *Frontiers in human neuroscience*, vol. 9, p. 525, 2015.
- [142] N. Esposito, "A short and simple definition of what a videogame is," in *Proceedings of DiGRA 2005 Conference: Changing Views: Worlds in Play*, 2005.
- [143] B. G. C. Esteves, "Personality assessment based on biosignals during a decision-making task," Ph.D. dissertation, 2017.
- [144] T. Estrella, C. Alfonso, J. Ramos-Castro, A. Alsina, and L. Capdevila, "A serious game to self-regulate heart rate variability as a technique to manage arousal level through cardiorespiratory biofeedback: Development and pilot evaluation study," *JSF*, vol. 11, p. e46351, 2023.
- [145] L. Faes, A. Porta, and G. Nollo, "Surrogate data approaches to assess the significance of directed coherence: application to eeg activity propagation," in *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2009, pp. 6280–6283.
- [146] M. Falcon, S. Martikainen, V. Wikström, T. Makkonen, and K. Saarikivi, "Dispositional empathy as a driver of inter-individual neural phase synchrony," *Scientific Reports*, vol. 15, no. 1, pp. 1–13, 2025.

- [147] H. Farid and M. J. Bravo, "Perceptual discrimination of computer generated and photographic faces," *Digital Investigation*, vol. 8, no. 3-4, pp. 226–235, 2012.
- [148] K. D. Federmeier and S. Laszlo, "Time for meaning: Electrophysiology provides insights into the dynamics of representation and processing in semantic memory," *Psychology of learning and motivation*, vol. 51, pp. 1–44, 2009.
- [149] C. J. Ferguson, A. Gryshyna, J. S. Kim, E. Knowles, Z. Nadeem, I. Cardozo, C. Esser, V. Trebbi, and E. Willis, "Video games, frustration, violence, and virtual reality: Two studies," *British journal of social psychology*, vol. 61, no. 1, pp. 83–99, 2022.
- [150] C. J. Ferguson, "The good, the bad and the ugly: A meta-analytic review of positive and negative effects of violent video games," *Psychiatric quarterly*, vol. 78, pp. 309–316, 2007.
- [151] L. Ferro, M. G. Monaci, and L. Scacchi, "Emotions and motivations of gambling: A comparison between scratch card, slot-machines, and casino gamblers," *Brain and Behavior*, vol. 14, no. 3, p. e3416, 2024.
- [152] A. Flinker, A. Korzeniewska, A. Y. Shestyuk, P. J. Franaszczuk, N. F. Dronkers, R. T. Knight, and N. E. Crone, "Redefining the role of broca's area in speech," *Proceedings of the National Academy of Sciences*, vol. 112, no. 9, pp. 2871–2875, 2015.
- [153] S. for Psychophysiological Research Ad Hoc Committee on Electrodermal Measures, W. Boucsein, D. C. Fowles, S. Grimnes, G. Ben-Shakhar, W. T. Roth, M. E. Dawson, and D. L. Filion, "Publication recommendations for electrodermal measurements," *Psychophysiology*, vol. 49, no. 8, pp. 1017–1034, 2012.
- [154] J. P. Forgas and R. East, "On being happy and gullible: Mood effects on skepticism and the detection of deception," *Journal of Experimental Social Psychology*, vol. 44, no. 5, pp. 1362–1367, 2008.
- [155] G. Forte, F. Favieri, and M. Casagrande, "Heart rate variability and cognitive function: A systematic review," *Frontiers in neuroscience*, vol. 13, p. 710, 2019.
- [156] D. Freedberg and V. Gallese, "Motion, emotion and empathy in esthetic experience," *Trends in cognitive sciences*, vol. 11, no. 5, pp. 197–203, 2007.
- [157] F. G. Freeman, P. J. Mikulka, M. W. Scerbo, and L. A. Scott, "Eeg-based indices of cognitive workload: A review," *Human Factors*, vol. 56, no. 3, pp. 401–413, 2014.
- [158] G. A. Frishkoff, D. M. Tucker, C. Davey, and M. Scherg, "Frontal and posterior sources of event-related potentials in semantic comprehension," *Cognitive Brain Research*, vol. 20, no. 3, pp. 329–354, 2004.

- [159] G. Froggio and M. Lori, "Deviance among young italians: investigating the predictive strength of value systems," *International journal of offender therapy and comparative criminology*, vol. 54, no. 4, pp. 581–596, 2010.
- [160] M. Frutos-Pascual and B. Garcia-Zapirain, "Assessing visual attention using eye tracking sensors in intelligent cognitive therapies based on serious games," *Sensors*, vol. 15, no. 5, pp. 11 092–11 117, 2015.
- [161] M. Fülöp, "Happy and unhappy competitors: What makes the difference?" *Psihologijske teme*, vol. 18, no. 2, pp. 345–367, 2009.
- [162] D. Gabana, L. Tokarchuk, E. Hannon, and H. Gunes, "Effects of valence and arousal on working memory performance in virtual reality gaming," in *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE, 2017, pp. 36–41.
- [163] L. J. Gabard-Durnam, A. S. Mendez Leal, C. L. Wilkinson, and A. R. Levin, "harvard automated pre-processing pipeline for eeg," github. [online], <https://github.com/lcnhappe/happe>, accessed: 21-Feb-2026.
- [164] —, "The harvard automated processing pipeline for electroencephalography (happe): standardized processing software for developmental and high-artifact data," *Frontiers in neuroscience*, vol. 12, p. 97, 2018.
- [165] J. D. Gabrieli, R. A. Poldrack, and J. E. Desmond, "The role of left prefrontal cortex in language and memory," *Proceedings of the national Academy of Sciences*, vol. 95, no. 3, pp. 906–913, 1998.
- [166] R. D. García-Ramón, E. J. Rechy-Ramirez, L. M. Alonso-Valerdi, and A. Marin-Hernandez, "Engagement analysis using electroencephalography signals in games for hand rehabilitation with dynamic and random difficulty adjustments," *Applied Sciences*, vol. 14, no. 18, p. 8464, 2024.
- [167] D. Ghimire, S. Jeong, J. Lee, and S. H. Park, "Facial expression recognition based on local region specific features and support vector machines," *Multimedia Tools and Applications*, vol. 76, pp. 7803–7821, 2017.
- [168] C. L. Giddens, K. W. Barron, J. Byrd-Craven, K. F. Clark, and A. S. Winter, "Vocal indices of stress: a review," *Journal of voice*, vol. 27, no. 3, pp. 390–e21, 2013.
- [169] A. Golberger, "Non-linear dynamics for clinicians: chaos theory, fractals, and complexity at the bedside," *The Lancet*, vol. 347, no. 9011, pp. 1312–1314, 1996.
- [170] A. L. Goldberger, L. A. Amaral, J. M. Hausdorff, P. C. Ivanov, C.-K. Peng, and H. E. Stanley, "Fractal dynamics in physiology: alterations with disease and aging," *Proceedings of the national academy of sciences*, vol. 99, no. suppl.1, pp. 2466–2472, 2002.

- [171] Y. Golland, Y. Arzouan, and N. Levit-Binnun, "The mere co-presence: Synchronization of autonomic signals and emotional responses across co-present individuals not engaged in direct interaction," *PloS one*, vol. 10, no. 5, p. e0125804, 2015.
- [172] I. Granic, A. Lobel, and R. C. Engels, "The benefits of playing video games." *American psychologist*, vol. 69, no. 1, p. 66, 2014.
- [173] B. Grässler, M. Dordevic, S. Darius, F. Herold, G. Forte, C. Langhans, N. Halfpaap, P. Müller, W. Glanz, E. H. M. Dantas *et al.*, "Is there a link between heart rate variability and cognitive decline? a cross-sectional study on patients with mild cognitive impairment and cognitively healthy controls," *Arquivos de Neuro-psiquiatria*, vol. 81, no. 01, pp. 009–018, 2023.
- [174] A. Greco, A. Lanata, L. Citi, N. Vanello, G. Valenza, and E. P. Scilingo, "Skin admittance measurement for emotion recognition: A study over frequency sweep," *Electronics*, vol. 5, no. 3, p. 46, 2016.
- [175] A. Greco, G. Valenza, A. Lanata, G. Rota, and E. P. Scilingo, "Electrodermal activity in bipolar patients during affective elicitation," *IEEE Journal of Biomedical and health Informatics*, vol. 18, no. 6, pp. 1865–1873, 2014.
- [176] A. Greco, G. Valenza, A. Lanata, E. P. Scilingo, and L. Citi, "cvxeda: A convex optimization approach to electrodermal activity processing," *IEEE transactions on biomedical engineering*, vol. 63, no. 4, pp. 797–804, 2015.
- [177] R. L. Greenbaum, T. W. Gray, A. D. Hill, M. Lima, S. S. Royce, and A. A. Smales, "Coworker narcissism: Employee emotional and behavioral reactions as moderated by bottom-line mentality and trait competitiveness," *Journal of Management*, vol. 50, no. 4, pp. 1295–1330, 2024.
- [178] N. Gullett, Z. Zajkowska, A. Walsh, R. Harper, and V. Mondelli, "Heart rate variability (hrv) as a way to understand associations between the autonomic nervous system (ans) and affective states: A critical review of the literature," *International Journal of Psychophysiology*, vol. 192, pp. 35–42, 2023.
- [179] M. C. Gursesli, F. Calà, P. Tarchi, L. Frassinetti, A. Guazzini, and A. Lanatà, "Eyetracking correlated in the matching pairs game," in *2023 IEEE Gaming, Entertainment, and Media Conference (GEM)*. IEEE, 2023, pp. 1–6.
- [180] M. C. Gursesli, S. Lombardi, M. Duradoni, L. Bocchi, A. Guazzini, and A. Lanata, "Facial emotion recognition (fer) through custom lightweight cnn model: performance evaluation in public datasets," *IEEE Access*, vol. 12, pp. 45 543–45 559, 2024.
- [181] M. C. Gursesli, A. Martucci, A. D. Mattiassi, M. Duradoni, and A. Guazzini, "Development and validation of the psychological motivations for playing video games scale (pmpvgs)," *Simulation & Gaming*, p. 10468781241260861, 2024.

- [182] M. C. Gursesli, P. Tarchi, F. Calá, L. Frassinetti, A. Guazzini, M. Duradoni, K. Park, R. Thawonmas, X. You, and A. Lanata, "Multimodal analysis of emotions in gaming: Understanding cultural influences," *IEEE Transactions on Affective Computing*, 2026.
- [183] M. C. Gursesli, P. Taveekitworachai, F. Abdullah, M. F. Dewantoro, A. Lanata, A. Guazzini, V. K. Lê, A. Villars, and R. Thawonmas, "The chronicles of chatgpt: generating and evaluating visual novel narratives on climate change through chatgpt," in *International Conference on Interactive Digital Storytelling*. Springer, 2023, pp. 181–194.
- [184] A. Hall, K. Kawai, K. Graber, G. Spencer, C. Roussin, P. Weinstock, and M. S. Volk, "Acoustic analysis of surgeons' voices to assess change in the stress response during surgical in situ simulation," *BMJ Simulation & Technology Enhanced Learning*, vol. 7, no. 6, p. 471, 2021.
- [185] J. Halpern, "What is clinical empathy?" *Journal of general internal medicine*, vol. 18, pp. 670–674, 2003.
- [186] J. Hamari, J. Koivisto, and H. Sarsa, "Does gamification work?—a literature review of empirical studies," in *47th Hawaii International Conference on System Sciences*. IEEE, 2014, pp. 3025–3034.
- [187] A. Hanandeh, S. Ayasrah, and W. Al Eid, "Impact of 'help! serious game' on motivation and achievement: A study on undergraduate students majoring in special education," *International Journal of Information and Education Technology*, vol. 14, no. 9, pp. 1306–1316, 2024.
- [188] M. Hardmeier, F. Hatz, H. Bousleiman, C. Schindler, C. J. Stam, and P. Fuhr, "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*, vol. 9, no. 10, p. e108648, 2014.
- [189] I. M. Haresign, E. Phillips, M. Whitehorn, L. Goupil, V. Noreika, V. Leong, and S. Wass, "Measuring the temporal dynamics of inter-personal neural entrainment in continuous child-adult eeg hyperscanning data," *Developmental cognitive neuroscience*, vol. 54, p. 101093, 2022.
- [190] R. Hari and M. V. Kujala, "Brain basis of human social interaction: from concepts to brain imaging," *Physiological reviews*, vol. 89, no. 2, pp. 453–479, 2009.
- [191] T. Harmony, "The functional significance of delta oscillations in cognitive processing," *Frontiers in integrative neuroscience*, vol. 7, p. 83, 2013.
- [192] H. Hartmann, E. M. Orlando, K. Borja, C. Keyzers, and V. Gazzola, "Cognitive control: exploring the causal role of the rtpj in empathy for pain mediated by contextual information," *Social Cognitive and Affective Neuroscience*, vol. 19, no. 1, p. nsae057, 2024.

- [193] H. Hassani, E. S. Silva, S. Unger, M. TajMazinani, and S. Mac Feely, “Artificial intelligence (ai) or intelligence augmentation (ia): what is the future?” *Ai*, vol. 1, no. 2, p. 8, 2020.
- [194] J. V. Haxby, E. A. Hoffman, and M. I. Gobbini, “The distributed human neural system for face perception,” *Trends in cognitive sciences*, vol. 4, no. 6, pp. 223–233, 2000.
- [195] R. L. Hazlett, “Measuring emotional valence during interactive experiences: boys at video game play,” in *Proceedings of the SIGCHI conference on Human Factors in computing systems*, 2006, pp. 1023–1026.
- [196] R. G. Heimberg, G. P. Mueller, C. S. Holt, D. A. Hope, and M. R. Liebowitz, “Assessment of anxiety in social interaction and being observed by others: The social interaction anxiety scale and the social phobia scale,” *Behavior therapy*, vol. 23, no. 1, pp. 53–73, 1992.
- [197] S. H. Hemenover and N. D. Bowman, “Video games, emotion, and emotion regulation: Expanding the scope,” *Ann Int Commun Assoc*, vol. 42, no. 2, pp. 125–143, 2018.
- [198] J. M. Henkel and V. B. Hinsz, “Success and failure in goal attainment as a mood induction procedure,” *Social Behavior and Personality: an international journal*, vol. 32, no. 8, pp. 715–722, 2004.
- [199] C. Herrmann, M. Grigutsch, N. Busch, and T. C. Handy, “Event-related potentials: a methods handbook,” *Todd Handy (Ed.)*, pp. 229–259, 2005.
- [200] J. Hirsch, X. Zhang, J. A. Noah, and Y. Ono, “Frontal temporal and parietal systems synchronize within and across brains during live eye-to-eye contact,” *NeuroImage*, vol. 157, pp. 314–330, 2017.
- [201] K. Hoemann, Z. Khan, M. J. Feldman, C. Nielson, M. Devlin, J. Dy, L. F. Barrett, J. B. Wormwood, and K. S. Quigley, “Context-aware experience sampling reveals the scale of variation in affective experience,” *Scientific reports*, vol. 10, no. 1, p. 12459, 2020.
- [202] O. Holmes, M. S. Banks, and H. Farid, “Assessing and improving the identification of computer-generated portraits,” *ACM Transactions on Applied Perception (TAP)*, vol. 13, no. 2, pp. 1–12, 2016.
- [203] A. Horvers, N. Tombeng, T. Bosse, A. W. Lazonder, and I. Molenaar, “Detecting emotions through electrodermal activity in learning contexts: A systematic review,” *Sensors*, vol. 21, no. 23, p. 7869, 2021.
- [204] J. Howarth, “How many gamers are there?(new 2023 statistics),” *Exploding Topics*, vol. 10, 2023.
- [205] D.-L. Hsieh and T.-C. Hsiao, “Heart rate variability of internet gaming disorder addicts in emotional states,” in *2016 International Conference on Biomedical Engineering (BME-HUST)*. IEEE, 2016, pp. 155–158.

- [206] D. Iacono, G. Rossi, and F. Vitali, "Integration between serious games and eeg signals: A systematic review," *Applied Sciences*, vol. 15, no. 4, p. 1946, 2025.
- [207] A. Inui, "The competitive structure of school and the labour market: Japan and Britain," *British Journal of Sociology of Education*, vol. 14, no. 3, pp. 301–313, 1993.
- [208] C. E. Izard, "Facial expressions and the regulation of emotions," *Journal of personality and social psychology*, vol. 58, no. 3, p. 487, 1990.
- [209] L. R. Izquierdo, S. S. Izquierdo, J. M. Galan, and J. I. Santos, "Techniques to understand computer simulations: Markov chain analysis," *Journal of Artificial Societies and Social Simulation*, vol. 12, no. 1, p. 6, 2009.
- [210] R. E. Jack, O. G. Garrod, H. Yu, R. Caldara, and P. G. Schyns, "Facial expressions of emotion are not culturally universal," *Proceedings of the National Academy of Sciences*, vol. 109, no. 19, pp. 7241–7244, 2012.
- [211] M. C. Jackson and J. E. Raymond, "The role of attention and familiarity in face identification," *Perception & Psychophysics*, vol. 68, pp. 543–557, 2006.
- [212] W. James, "The emotions." 1922.
- [213] P. Jerčić, "Arousal measurement reflected in the pupil diameter for a decision-making performance in serious games," in *Joint International Conference on Entertainment Computing and Serious Games*. Springer, 2019, pp. 287–298.
- [214] Y. Jiang, H. Zhang, and S. Yu, "Changes in delta and theta oscillations in the brain indicate dynamic switching of attention between internal and external processing," in *4th International Conference on Biometric Engineering and Applications*, 2021, pp. 25–31.
- [215] C. Jones, L. Scholes, D. Johnson, M. Katsikitis, and M. C. Carras, "Gaming well: links between videogames and flourishing mental health," *Frontiers in psychology*, vol. 5, p. 76833, 2014.
- [216] J. Juvrud, G. Ansgariusson, P. Selleby, and M. Johansson, "Game or watch: The effect of interactivity on arousal and engagement in video game media," *IEEE Transactions on Games*, vol. 14, no. 2, pp. 308–317, 2021.
- [217] H. Kantz and T. Schreiber, *Nonlinear time series analysis*. Cambridge university press, 2003.
- [218] N. Kanwisher and G. Yovel, "The fusiform face area: a cortical region specialized for the perception of faces," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 361, no. 1476, pp. 2109–2128, 2006.

- [219] D. Karamacoska, R. J. Barry, and G. Z. Steiner, "Electrophysiological underpinnings of response variability in the go/nogo task," *International Journal of Psychophysiology*, vol. 134, pp. 159–167, 2018.
- [220] D. Karamacoska, R. J. Barry, G. Z. Steiner, E. P. Coleman, and E. J. Wilson, "Intrinsic eeg and task-related changes in eeg affect go/nogo task performance," *International Journal of Psychophysiology*, vol. 125, pp. 17–28, 2018.
- [221] R. Karani, J. Jani, and S. Desai, "Fer-bharat: a lightweight deep learning network for efficient unimodal facial emotion recognition in indian context," *Discover Artificial Intelligence*, vol. 4, no. 1, p. 35, 2024.
- [222] K. Karpouzis, G. N. Yannakakis, N. Shaker, and S. Asteriadis, "The platformer experience dataset," in *2015 International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE, 2015, pp. 712–718.
- [223] P. M. Kato, "Video games in health care: Closing the gap," *Review of general psychology*, vol. 14, no. 2, pp. 113–121, 2010.
- [224] H. Kawabata and S. Zeki, "Neural correlates of beauty," *Journal of neurophysiology*, vol. 91, no. 4, pp. 1699–1705, 2004.
- [225] J. Kim and E. André, "Emotion recognition based on physiological changes in music listening," *IEEE transactions on pattern analysis and machine intelligence*, vol. 30, no. 12, pp. 2067–2083, 2008.
- [226] K. Kim, "An exploratory study on the emotion in korean school children," *The Korean Journal of Developmental Psychology*, vol. 10, no. 1, pp. 43–46, 1997.
- [227] K. H. Kim, "An exploratory study on the emotion in korean adolescents." *Korean Journal of Developmental Psychology*, 1996.
- [228] S. Y. Kim, "Do asian values exist? empirical tests of the four dimensions of asian values," *Journal of East Asian Studies*, vol. 10, no. 2, pp. 315–344, 2010.
- [229] Y. Kim, "The body, tv talk, and emotion: Methodological reflections," *Cultural Studies? Critical Methodologies*, vol. 6, no. 2, pp. 226–244, 2006.
- [230] E. G. Kirby and J. K. Ross III, "Kiasu tendency and tactics: A study of their impact on task performance." *Journal of Behavioral & Applied Management*, vol. 8, no. 2, 2007.
- [231] W. Klimesch, "Alpha-band oscillations, attention, and controlled access to stored information," *Trends in cognitive sciences*, vol. 16, no. 12, pp. 606–617, 2012.

- [232] G. G. Knyazev, K. A. Barchard, O. M. Razumnikova, and L. G. Mitrofanova, "The relationship of positive and negative expressiveness to the processing of emotion information," *Scandinavian journal of psychology*, vol. 53, no. 3, pp. 206–215, 2012.
- [233] T. Koelewijn, H. de Kluiver, B. G. Shinn-Cunningham, A. A. Zekveld, and S. E. Kramer, "The pupil response reveals increased listening effort when it is difficult to focus attention," *Hear Res*, vol. 323, pp. 81–90, 2015.
- [234] K. Koller-Schlaud, J. Querbach, J. Behr, A. Ströhle, and J. Rentzsch, "Test-retest reliability of frontal and parietal alpha asymmetry during presentation of emotional face stimuli in healthy subjects," *Neuropsychobiology*, vol. 79, no. 6, pp. 428–436, 2020.
- [235] K. Konrad, C. Gerloff, S. H. Kohl, D. M. Mehler, L. Mehlem, E. L. Volbert, M. Komorek, A. T. Henn, M. Boecker, E. Weiss *et al.*, "Interpersonal neural synchrony and mental disorders: unlocking potential pathways for clinical interventions," *Frontiers in Neuroscience*, vol. 18, p. 1286130, 2024.
- [236] P. Korshunov and S. Marcel, "Deepfake detection: humans vs. machines," *arXiv preprint arXiv:2009.03155*, 2020.
- [237] T. L. Kraft and S. D. Pressman, "Grin and bear it: The influence of manipulated facial expression on the stress response," *Psychological science*, vol. 23, no. 11, pp. 1372–1378, 2012.
- [238] I. Kraminick, "Reflections on revolution: Definition and explanation in recent scholarship," *History and Theory*, vol. 11, no. 1, pp. 26–63, 1972.
- [239] M. Krcmar, K. M. Farrar, G. Jalette, and R. McGloin, "Appetitive and defensive arousal in violent video games: Explaining individual differences in attraction to and effects of video games," *Media psychology*, vol. 18, no. 4, pp. 527–550, 2015.
- [240] S. D. Kreibig, "Autonomic nervous system activity in emotion: A review," *Biological psychology*, vol. 84, no. 3, pp. 394–421, 2010.
- [241] M. E. Kret and E. E. Sjak-Shie, "Preprocessing pupil size data: Guidelines and code," *Behavior research methods*, vol. 51, no. 3, pp. 1336–1342, 2019.
- [242] M. Kutas and K. D. Federmeier, "Thirty years and counting: finding meaning in the n400 component of the event-related brain potential (erp)," *Annual review of psychology*, vol. 62, pp. 621–647, 2011.
- [243] J.-P. Lachaux, E. Rodriguez, J. Martinerie, and F. J. Varela, "Measuring phase synchrony in brain signals," *Human brain mapping*, vol. 8, no. 4, pp. 194–208, 1999.
- [244] M. Lahbiri, A. Fnaiech, M. Bouchouicha, M. Sayadi, and P. Gorce, "Facial emotion recognition with the hidden markov model," in *2013 International*

- Conference on Electrical Engineering and Software Applications*. IEEE, 2013, pp. 1–6.
- [245] A. Lanatà, A. Armato, G. Valenza, and E. P. Scilingo, “Eye tracking and pupil size variation as response to affective stimuli: a preliminary study,” in *2011 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*. IEEE, 2011, pp. 78–84.
- [246] A. Lanatà, A. Greco, M. Ciardelli, A. Uvelli, E. Fratini, D. Manzoni, E. P. Scilingo, E. L. Santarcangelo, and L. Sebastiani, “Linear and non linear measures of pupil size as a function of hypnotizability,” *Sci Rep*, vol. 11, no. 1, p. 5196, 2021.
- [247] A. Lanata, A. Greco, G. Valenza, and E. P. Scilingo, “A pattern recognition approach based on electrodermal response for pathological mood identification in bipolar disorders,” in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2014, pp. 3601–3605.
- [248] A. Lanata, G. Valenza, and E. P. Scilingo, “A novel eda glove based on textile-integrated electrodes for affective computing,” *Medical & biological engineering & computing*, vol. 50, pp. 1163–1172, 2012.
- [249] —, “Eye gaze patterns in emotional pictures,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 4, no. 6, pp. 705–715, 2013.
- [250] P. J. Lang, M. M. Bradley, B. N. Cuthbert *et al.*, “International affective picture system (iaps): Technical manual and affective ratings,” *NIMH Center for the Study of Emotion and Attention*, vol. 1, no. 39-58, p. 3, 1997.
- [251] —, “International affective picture system (iaps): Technical manual and affective ratings,” *NIMH Center for the Study of Emotion and Attention*, vol. 1, no. 39-58, p. 3, 1997.
- [252] S.-Y. J. Lau and H. Agius, “A framework and immersive serious game for mild cognitive impairment,” *Multimedia Tools and Applications*, vol. 80, no. 20, pp. 31 183–31 237, 2021.
- [253] S. Lautenbacher, T. Hassan, D. Seuss, F. W. Loy, J.-U. Garbas, U. Schmid, and M. Kunz, “Automatic coding of facial expressions of pain: Are we there yet?” *Pain Research and Management*, vol. 2022, no. 1, p. 6635496, 2022.
- [254] A. Lavazza, “Neuroestetica,” Dec. 2003, intervista al neurobiologo Semir Zeki. [Online]. Available: <https://www.carmillaonline.com/2003/12/11/neuroestetica/>
- [255] M. Lázaro, V. Illera, S. García, and J. M. R. S. de León, “Morphological processing of complex and simple pseudo-words in adults and older adults,” *Language and Cognition*, vol. 14, no. 3, pp. 385–400, 2022.

- [256] T. Le Mau, K. Hoemann, S. H. Lyons, J. M. Fugate, E. N. Brown, M. Gendron, and L. F. Barrett, "Professional actors demonstrate variability, not stereotypical expressions, when portraying emotional states in photographs," *Nature communications*, vol. 12, no. 1, p. 5037, 2021.
- [257] J. Lebowitz and C. Klug, *Interactive storytelling for video games: A player-centered approach to creating memorable characters and stories*. Taylor & Francis, 2012.
- [258] J. LeDoux, "Rethinking the emotional brain," *Neuron*, vol. 73, no. 4, pp. 653–676, 2012.
- [259] J. E. LeDoux, *The emotional brain: The mysterious underpinnings of emotional life*. Simon and Schuster, 1996.
- [260] —, "Cognitive-emotional interactions," *Cognitive neuroscience of emotion*, pp. 129–155, 2000.
- [261] H.-h. Lee, E.-J. Kim, and M.-k. Lee, "A validation study of korea positive and negative affect schedule: The panas scales," *Korean Journal of Clinical Psychology*, vol. 22, no. 4, pp. 935–946, 2003.
- [262] J. Lee, K. Luchini, B. Michael, C. Norris, and E. Soloway, "More than just fun and games: Assessing the value of educational video games in the classroom," in *CHI'04 extended abstracts on Human factors in computing systems*, 2004, pp. 1375–1378.
- [263] B. Lelonek-Kuleta, R. P. Bartczuk, M.-L. Tovar, E. Benoit, and J.-M. Costes, "Experiencing a significant win and its sociodemographic and motivational predictors: A comparative analysis of pure-chance gamblers from poland and france," *Plos one*, vol. 17, no. 11, p. e0277972, 2022.
- [264] J. S. Lemmens, P. M. Valkenburg, and J. Peter, "The effects of pathological gaming on aggressive behavior," *Journal of youth and adolescence*, vol. 40, pp. 38–47, 2011.
- [265] J. M. Leppänen, M. C. Moulson, V. K. Vogel-Farley, and C. A. Nelson, "An erp study of emotional face processing in the adult and infant brain," *Child development*, vol. 78, no. 1, pp. 232–245, 2007.
- [266] J. S. Lerner, Y. Li, P. Valdesolo, and K. S. Kassam, "Emotion and decision making," *Annual review of psychology*, vol. 66, no. 1, pp. 799–823, 2015.
- [267] M. Leyer and S. Schneider, "Decision augmentation and automation with artificial intelligence: Threat or opportunity for managers?" *Business Horizons*, vol. 64, no. 5, pp. 711–724, 2021.
- [268] Q. Li, M. Zimmermann, and I. Konvalinka, "Two-brain microstates: A novel hyperscanning-erp method for quantifying task-driven inter-brain asymmetry," *Journal of Neuroscience Methods*, p. 110355, 2025.

- [269] R. Li, X. Jia, C. Zhou, and J. Zhang, "Reconfiguration of the brain during aesthetic experience on chinese calligraphy - using brain complex networks," *Visual Informatics*, vol. 6, no. 1, pp. 35–46, 2022.
- [270] S. Li and W. Deng, "Reliable crowdsourcing and deep locality-preserving learning for unconstrained facial expression recognition," *IEEE Transactions on Image Processing*, vol. 28, no. 1, pp. 356–370, 2019.
- [271] S. Li, W. Deng, and J. Du, "Reliable crowdsourcing and deep locality-preserving learning for expression recognition in the wild," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2017, pp. 2584–2593.
- [272] G. A. Light, L. E. Williams, F. Minow, J. Sprock, A. Rissling, R. Sharp, N. R. Swerdlow, and D. L. Braff, "Electroencephalography (eeg) and event-related potentials (erps) with human participants," *Current protocols in neuroscience*, vol. 52, no. 1, pp. 6–25, 2010.
- [273] J.-C. Lin, C.-H. Wu, and W.-L. Wei, "Error weighted semi-coupled hidden markov model for audio-visual emotion recognition," *IEEE Transactions on Multimedia*, vol. 14, no. 1, pp. 142–156, 2011.
- [274] C. Liu, P. Agrawal, N. Sarkar, and S. Chen, "Dynamic difficulty adjustment in computer games through real-time anxiety-based affective feedback," *International Journal of Human-Computer Interaction*, vol. 25, no. 6, pp. 506–529, 2009.
- [275] Z. Liu, W. Du, Z. Sun, G. Hou, and Z. Wang, "Neural processing differences of facial emotions between human and vehicles: Evidence from an event-related potential study," *Frontiers in Psychology*, vol. 13, p. 876252, 2022.
- [276] P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, and I. Matthews, "The extended cohn-kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression," in *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition-Workshops*. IEEE, 2010, pp. 94–101.
- [277] S. J. Luck, *An introduction to the event-related potential technique*. MIT press, 2014.
- [278] W. Luo, W. Feng, W. He, N.-Y. Wang, and Y.-J. Luo, "Three stages of facial expression processing: Erp study with rapid serial visual presentation," *Neuroimage*, vol. 49, no. 2, pp. 1857–1867, 2010.
- [279] M. J. Lyons, "'excavating ai' re-excavated: debunking a fallacious account of the jaffe dataset," *arXiv preprint arXiv:2107.13998*, 2021.
- [280] M. J. Lyons, M. Kamachi, and J. Gyoba, "Coding facial expressions with gabor wavelets (ivc special issue)," *arXiv preprint arXiv:2009.05938*, 2020.

- [281] D. M. Mackie, T. Devos, and E. R. Smith, "Intergroup emotions: explaining offensive action tendencies in an intergroup context." *Journal of personality and social psychology*, vol. 79, no. 4, p. 602, 2000.
- [282] A. Mackinnon, A. F. Jorm, H. Christensen, A. E. Korten, P. A. Jacomb, and B. Rodgers, "A short form of the positive and negative affect schedule: Evaluation of factorial validity and invariance across demographic variables in a community sample," *Personality and Individual differences*, vol. 27, no. 3, pp. 405–416, 1999.
- [283] B. Mader, M. S. Banks, and H. Farid, "Identifying computer-generated portraits: The importance of training and incentives," *Perception*, vol. 46, no. 9, pp. 1062–1076, 2017.
- [284] D. Maida, "Musei e neuroscienza: Alle gallerie d'italia di milano studiano le reazioni emotive del pubblico," Apr. 2018, artribune, 03 April 2018. [Online]. Available: <https://www.artribune.com/progettazione/new-media/2018/04/musei-neuroscienza-gallerie-ditalia-milano-studio-reazioni-emotive-pubblico/>
- [285] A. Makrushin, D. Siegel, and J. Dittmann, "Simulation of border control in an ongoing web-based experiment for estimating morphing detection performance of humans," in *Proceedings of the 2020 ACM Workshop on Information Hiding and Multimedia Security*, 2020, pp. 91–96.
- [286] S. Mao, D. Tao, G. Zhang, P. Ching, and T. Lee, "Revisiting hidden markov models for speech emotion recognition," in *ICASSP 2019-2019 IEEE international conference on acoustics, speech and signal processing (ICASSP)*. IEEE, 2019, pp. 6715–6719.
- [287] C. Marinetti, P. Moore, P. Lucas, and B. Parkinson, "Emotions in social interactions: Unfolding emotional experience," *Emotion-oriented systems: The humane handbook*, pp. 31–46, 2011.
- [288] K. Marinkovic, S. Baldwin, M. G. Courtney, T. Witzel, A. M. Dale, and E. Halgren, "Right hemisphere has the last laugh: neural dynamics of joke appreciation," *Cognitive, Affective, & Behavioral Neuroscience*, vol. 11, pp. 113–130, 2011.
- [289] L. A. Martínez-Tejada, A. P. González, N. Yoshimura, and Y. Koike, "Videogame design as a elicit tool for emotion recognition experiments," in *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2020, pp. 4320–4326.
- [290] A. Martucci, M. C. Gursesli, M. Duradoni, A. Guazzini *et al.*, "Overviewing gaming motivation and its associated psychological and sociodemographic variables: A prisma systematic review," *Human Behavior and Emerging Technologies*, vol. 2023, 2023.

- [291] H. Marzbani, H. R. Marateb, and M. Mansourian, "Neurofeedback: a comprehensive review on system design, methodology and clinical applications," *Basic and clinical neuroscience*, vol. 7, no. 2, p. 143, 2016.
- [292] C. Marzi, A. Greco, E. P. Scilingo, and N. Vanello, "Towards a model of arousal change after affective word pronunciation based on electrodermal activity and speech analysis," *Biomedical Signal Processing and Control*, vol. 67, p. 102517, 2021.
- [293] S. Marzillier and G. Davey, "The emotional profiling of disgust-eliciting stimuli: Evidence for primary and complex disgusts," *Cognition and Emotion*, vol. 18, no. 3, pp. 313–336, 2004.
- [294] S. Mathôt, "Pupillometry: Psychology, physiology, and function," *J Cogn*, vol. 1, no. 1, 2018.
- [295] A. Matsumoto, Y. Ichikawa, N. Kanayama, H. Ohira, and T. Iidaka, "Gamma band activity and its synchronization reflect the dysfunctional emotional processing in alexithymic persons," *Psychophysiology*, vol. 43, no. 6, pp. 533–540, 2006.
- [296] D. Matsumoto and P. Ekman, "American-japanese cultural differences in intensity ratings of facial expressions of emotion," *Motivation and emotion*, vol. 13, pp. 143–157, 1989.
- [297] D. Matsumoto, S. Takeuchi, S. Andayani, N. Kouznetsova, and D. Krupp, "The contribution of individualism vs. collectivism to cross-national differences in display rules," *Asian journal of social psychology*, vol. 1, no. 2, pp. 147–165, 1998.
- [298] D. Matsumoto, S. H. Yoo, and S. Nakagawa, "Culture, emotion regulation, and adjustment," *Journal of personality and social psychology*, vol. 94, no. 6, p. 925, 2008.
- [299] M. Matyjek, B. Kroczeck, and M. Senderecka, "Socially induced negative affective knowledge modulates early face perception but not gaze cueing of attention," *Psychophysiology*, vol. 58, no. 9, p. e13876, 2021.
- [300] I. B. Mauss, R. W. Levenson, L. McCarter, F. H. Wilhelm, and J. J. Gross, "The tie that binds? coherence among emotion experience, behavior, and physiology," *Emotion*, vol. 5, no. 2, p. 175, 2005.
- [301] N. McNew, "The eigenvalue gap and mixing time," -, 2011.
- [302] N. Mehendale, "Facial emotion recognition using convolutional neural networks (ferc)," *SN Applied Sciences*, vol. 2, no. 3, p. 446, 2020.
- [303] D. Melhart, A. Liapis, and G. N. Yannakakis, "The arousal video game annotation (again) dataset," *IEEE Transactions on Affective Computing*, vol. 13, no. 4, pp. 2171–2184, 2022.

- [304] H. M. Melo, A. A. Hoeller, R. Walz, and E. Takase, "Resting cardiac vagal tone is associated with long-term frustration level of mental workload: Ultra-short term recording reliability," *Applied Psychophysiology and Biofeedback*, vol. 45, pp. 1–9, 2020.
- [305] L. R. Mercado-Diaz, Y. R. Veeranki, F. Marmolejo-Ramos, and H. F. Posada-Quintero, "Eda-graph: Graph signal processing of electrodermal activity for emotional states detection," *IEEE Journal of Biomedical and Health Informatics*, 2024.
- [306] D. Metzen, E. Genç, S. Getzmann, M. F. Larra, E. Wascher, and S. Ocklenburg, "Frontal and parietal eeg alpha asymmetry: a large-scale investigation of short-term reliability on distinct eeg systems," *Brain Structure and Function*, vol. 227, no. 2, pp. 725–740, 2022.
- [307] V. I. Michalowski, D. Gerstorff, G. Hülür, J. Drewelies, M. C. Ashe, K. M. Madden, and C. A. Hoppmann, "Intraindividual variability and empathic accuracy for happiness in older couples," *GeroPsych*, 2020.
- [308] D. A. Miller, T. Cronin, A. L. Garcia, and N. R. Branscombe, "The relative impact of anger and efficacy on collective action is affected by feelings of fear," *Group Processes & Intergroup Relations*, vol. 12, no. 4, pp. 445–462, 2009.
- [309] L. M. Miller and J. Robertson, "Serious games for learning and health: evaluating the evidence," *Games for Health Journal*, vol. 3, no. 1, pp. 34–38, 2014.
- [310] P. Missonnier, M.-P. Deiber, G. Gold, P. Millet, M. Gex-Fabry Pun, L. Fazio-Costa, P. Giannakopoulos, and V. Ibáñez, "Frontal theta event-related synchronization: comparison of directed attention and working memory load effects," *Journal of neural transmission*, vol. 113, no. 10, pp. 1477–1486, 2006.
- [311] T. Miyatsu, B. M. Smith, A. P. Koutnik, P. Pirollo, and T. J. Broderick, "Resting-state heart rate variability after stressful events as a measure of stress tolerance among elite performers," *Frontiers in Physiology*, vol. 13, p. 1070285, 2023.
- [312] A. Mollahosseini, B. Hasani, and M. H. Mahoor, "Affectnet: A database for facial expression, valence, and arousal computing in the wild," *IEEE Transactions on Affective Computing*, vol. 10, no. 1, pp. 18–31, 2017.
- [313] A. Montagrin, V. Sterpenich, T. Brosch, D. Grandjean, J. Armony, L. Ceravolo, and D. Sander, "Goal-relevant situations facilitate memory of neutral faces," *Cognitive, Affective, & Behavioral Neuroscience*, vol. 18, pp. 1269–1282, 2018.

- [314] Q. Moreau, F. Brun, A. Ayrolles, J. Nadel, and G. Dumas, "Distinct social behavior and inter-brain connectivity in dyads with autistic individuals," *Social Neuroscience*, vol. 19, no. 2, pp. 124–136, 2024.
- [315] M. S. Morelli and S. O. C. Manfredi, "Biovoice: A multipurpose tool for voice analysis," in *Proceedings of the 11th International Workshop Models and Analysis of Vocal Emissions for Biomedical Applications, MAVEBA 2019*. Firenze University Press Firenze, Italy, 2019, pp. 261–264.
- [316] D. V. Moretti, C. Babiloni, G. Binetti, E. Cassetta, G. Dal Forno, F. Ferrer, R. Ferri, B. Lanuzza, C. Miniussi, F. Nobili *et al.*, "Individual analysis of eeg frequency and band power in mild alzheimer's disease," *Clinical Neurophysiology*, vol. 115, no. 2, pp. 299–308, 2004.
- [317] H. M. Morgan, C. Klein, S. G. Boehm, K. L. Shapiro, and D. E. Linden, "Working memory load for faces modulates p300, n170, and n250r," *Journal of cognitive neuroscience*, vol. 20, no. 6, pp. 989–1002, 2008.
- [318] P. Moschovitis and A. Denisova, "Keep calm and aim for the head: Biofeedback-controlled dynamic difficulty adjustment in a horror game," *IEEE Transactions on Games*, vol. 15, no. 3, pp. 368–377, 2022.
- [319] M. L. Moshel, A. K. Robinson, T. A. Carlson, and T. Grootswagers, "Are you for real? decoding realistic ai-generated faces from neural activity," *Vision Research*, vol. 199, p. 108079, 2022.
- [320] B. Mostefai, A. Balla, and P. Trigano, "A generic and efficient emotion-driven approach toward personalized assessment and adaptation in serious games," *Cognitive Systems Research*, vol. 56, pp. 82–106, 2019.
- [321] C. Mühl, B. Allison, A. Nijholt, and G. Chanel, "A survey of affective brain computer interfaces: Principles, state-of-the-art, and challenges," *Brain-Computer Interfaces*, vol. 1, no. 2, pp. 66–84, 2014.
- [322] T. Mullen, "Cleanline eeglab plugin," *San Diego, CA: Neuroimaging Informatics Tools and Resources Clearinghouse (NITRC)*, 2012.
- [323] M. Nardelli, A. Greco, L. Sebastiani, and E. P. Scilingo, "Comeda: A new tool for stress assessment based on electrodermal activity," *Computers in Biology and Medicine*, vol. 150, p. 106144, 2022.
- [324] N. N. M. Nazry and D. M. Romano, "Mood and learning in navigation-based serious games," *Computers in Human Behavior*, vol. 73, pp. 596–604, 2017.
- [325] N. J. Nilsson, *Principles of artificial intelligence*. Springer Science & Business Media, 1982.
- [326] M. Ninaus, K. Tsarava, and K. Moeller, "A pilot study on the feasibility of dynamic difficulty adjustment in game-based learning using heart-rate," in

- Games and Learning Alliance: 8th International Conference, GALA 2019, Athens, Greece, November 27–29, 2019, Proceedings 8.* Springer, 2019, pp. 117–128.
- [327] G. Novembre and G. D. Iannetti, “Hyperscanning alone cannot prove causality. multibrain stimulation can,” *Trends in Cognitive Sciences*, vol. 25, no. 2, pp. 96–99, 2021.
 - [328] L. Nummenmaa, E. Glerean, M. Viinikainen, I. P. Jääskeläinen, R. Hari, and M. Sams, “Emotions promote social interaction by synchronizing brain activity across individuals,” *Proceedings of the National Academy of Sciences*, vol. 109, no. 24, pp. 9599–9604, 2012.
 - [329] T. L. Nwe, S. W. Foo, and L. C. De Silva, “Speech emotion recognition using hidden markov models,” *Speech communication*, vol. 41, no. 4, pp. 603–623, 2003.
 - [330] U. D. of Health and H. S. (n.d.). (2016) Quick statistics about voice, speech, language. national institute of deafness and other communication disorders. [Online]. Available: <https://www.nidcd.nih.gov/health/statistics/quick-statistics-voice-speech-language>
 - [331] S. Oh and D.-K. Kim, “Comparative analysis of emotion classification based on facial expression and physiological signals using deep learning,” *Applied Sciences*, vol. 12, no. 3, p. 1286, 2022.
 - [332] H. Okon-Singer, L. Lichtenstein-Vidne, and N. Cohen, “Dynamic modulation of emotional processing,” *Biological psychology*, vol. 92, no. 3, pp. 480–491, 2013.
 - [333] B. O. Olatunji and C. N. Sawchuk, “Disgust: Characteristic features, social manifestations, and clinical implications,” *Journal of Social and Clinical Psychology*, vol. 24, no. 7, pp. 932–962, 2005.
 - [334] F. Olivieri, L. Biscetti, L. Pimpini, G. Pelliccioni, J. Sabbatinelli, and S. Giunta, “Heart rate variability and autonomic nervous system imbalance: Potential biomarkers and detectable hallmarks of aging and inflammaging,” *Ageing Research Reviews*, vol. 101, p. 102521, 2024.
 - [335] F. Onorati, L. T. Mainardi, F. Sirca, V. Russo, and R. Barbieri, “Nonlinear analysis of pupillary dynamics,” *BMT*, vol. 61, no. 1, pp. 95–106, 2016.
 - [336] J. Pan and W. J. Tompkins, “A real-time qrs detection algorithm,” *IEEE transactions on biomedical engineering*, no. 3, pp. 230–236, 1985.
 - [337] —, “A real-time qrs detection algorithm,” *IEEE transactions on biomedical engineering*, no. 3, pp. 230–236, 2007.
 - [338] J. Panksepp, “At the interface of the affective, behavioral, and cognitive neurosciences: Decoding the emotional feelings of the brain,” *Brain and cognition*, vol. 52, no. 1, pp. 4–14, 2003.

- [339] A. Parnandi and R. Gutierrez-Osuna, "Visual biofeedback and game adaptation in relaxation skill transfer," *IEEE Trans Affect Comput*, vol. 10, no. 2, pp. 276–289, 2017.
- [340] O. Pascalis and D. J. Kelly, "On the development of face processing," *Perspective on Psychological Science*, vol. 4, pp. 200–09, 2009.
- [341] D. L. Paulhus, S. Vazire *et al.*, "The self-report method," *Handbook of research methods in personality psychology*, vol. 1, no. 2007, pp. 224–239, 2007.
- [342] M. Pelowski, P. S. Markey, M. Forster, G. Gerger, and H. Leder, "Move me, astonish me... delight my eyes and brain: The vienna integrated model of top-down and bottom-up processes in art perception (vimap) and corresponding affective, evaluative, and neurophysiological correlates," *Physics of life reviews*, vol. 21, pp. 80–125, 2017.
- [343] A. Pérez, M. Carreiras, and J. A. Duñabeitia, "Brain-to-brain entrainment: Eeg interbrain synchronization while speaking and listening," *Scientific reports*, vol. 7, no. 1, p. 4190, 2017.
- [344] D. Pérez-Jorge, E. Olmos-Raya, I. Alonso-Rodríguez, and I. Pérez-Pérez, "Electrodermal response to olfactory stimuli in children with autism spectrum disorder: a systematic review of emotional and cognitive regulation," in *Frontiers in Education*, vol. 10. Frontiers Media SA, 2025, p. 1485252.
- [345] L. Pessoa, "On the relationship between emotion and cognition," *Nature reviews neuroscience*, vol. 9, no. 2, pp. 148–158, 2008.
- [346] —, "How do emotion and motivation direct executive control?" *Trends in cognitive sciences*, vol. 13, no. 4, pp. 160–166, 2009.
- [347] —, "Précis on the cognitive-emotional brain," *Behavioral and Brain Sciences*, vol. 38, p. e71, 2015.
- [348] V. C. Pezoulas, A. Athanasiou, G. Nolte, M. Zervakis, A. Fratini, D. I. Fotiadis, and M. A. Klados, "Fclab: An eeglab module for performing functional connectivity analysis on single-subject eeg data," in *2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*. IEEE, 2018, pp. 96–99.
- [349] S. M. Pincus, "Approximate entropy as a measure of system complexity." *Proceedings of the national academy of sciences*, vol. 88, no. 6, pp. 2297–2301, 1991.
- [350] R. Pine, A. Leung, and M. Collins, "Two sides of the same virtual coin: Stress relief motivations in gaming," *Healthcare*, vol. 12, no. 7, p. 772, 2024.
- [351] E. B. Prince, E. S. Kim, C. A. Wall, E. Gisin, M. S. Goodwin, E. S. Simmons, K. Chawarska, and F. Shic, "The relationship between autism symptoms

- and arousal level in toddlers with autism spectrum disorder, as measured by electrodermal activity,” *Autism*, vol. 21, no. 4, pp. 504–508, 2017.
- [352] S. Prot, K. A. McDonald, C. A. Anderson, and D. A. Gentile, “Video games:: Good, bad, or other?” *Pediatric Clinics*, vol. 59, no. 3, pp. 647–658, 2012.
- [353] A. K. Przybylski, C. S. Rigby, and R. M. Ryan, “A motivational model of video game engagement,” *Review of general psychology*, vol. 14, no. 2, pp. 154–166, 2010.
- [354] X. Qiao, R. Li, H. Huang, Y. Hong, X. Li, Z. Li, S. Chen, L. Yang, S. Ong, Y. Yao *et al.*, “Exploring the neural mechanisms underlying cooperation and competition behavior: Insights from stereo-electroencephalography hyper-scanning,” *iScience*, vol. 28, no. 2, 2025.
- [355] K. S. Quigley, P. J. Gianaros, G. J. Norman, J. R. Jennings, G. G. Berntson, and E. J. de Geus, “Publication guidelines for human heart rate and heart rate variability studies in psychophysiology-part 1: Physiological underpinnings and foundations of measurement,” *Psychophysiology*, vol. 61, no. 9, p. e14604, 2024.
- [356] P. Rainville, A. Bechara, N. Naqvi, and A. R. Damasio, “Basic emotions are associated with distinct patterns of cardiorespiratory activity,” *International journal of psychophysiology*, vol. 61, no. 1, pp. 5–18, 2006.
- [357] R. M. Rangayyan and N. P. Reddy, “Biomedical signal analysis: a case-study approach,” *Annals of Biomedical Engineering*, vol. 30, no. 7, pp. 983–983, 2002.
- [358] C. M. M. Refat and N. Z. Azlan, “Deep learning methods for facial expression recognition,” in *2019 7th International Conference on Mechatronics Engineering (ICOM)*. IEEE, 2019, pp. 1–6.
- [359] A. Ricci Maccarini and E. Lucchini, “La valutazione soggettiva ed oggettiva della disfonia. il protocollo sifel in ”relazione ufficiale al xxiv congresso nazionale della società italiana di foniatria e logopedia”,” *Acta Phon. Lat*, vol. 26, pp. 1–2, 2002.
- [360] J. S. Richman and J. R. Moorman, “Physiological time-series analysis using approximate entropy and sample entropy,” *American journal of physiology-heart and circulatory physiology*, vol. 278, no. 6, pp. H2039–H2049, 2000.
- [361] W. Rief, J. Heuser, and M. M. Fichter, “What does the toronto alexithymia scale tas-r measure?” *Journal of Clinical Psychology*, vol. 52, no. 4, pp. 423–429, 1996.
- [362] G. Rizzolatti and L. Craighero, “The mirror-neuron system,” *Annu. Rev. Neurosci.*, vol. 27, no. 1, pp. 169–192, 2004.

- [363] M. Rodemer, J. Karch, and S. Bernholt, "Pupil dilation as cognitive load measure in instructional videos on complex chemical representations," in *Frontiers in Education*, vol. 8. Frontiers Media SA, 2023, p. 1062053.
- [364] I. J. Roseman, "Cognitive determinants of emotion: A structural theory." *Review of personality & social psychology*, 1984.
- [365] P. Rozin and A. E. Fallon, "A perspective on disgust." *Psychological review*, vol. 94, no. 1, p. 23, 1987.
- [366] M. Rubinov, R. Kötter, P. Hagmann, and O. Sporns, "Brain connectivity toolbox: a collection of complex network measurements and brain connectivity datasets." *NeuroImage*, vol. 47, p. S169, 2009.
- [367] J. A. Russell, "A circumplex model of affect." *Journal of personality and social psychology*, vol. 39, no. 6, p. 1161, 1980.
- [368] C. V. Russoniello, M. T. Fish, and K. O'Brien, "The efficacy of playing videogames compared with antidepressants in reducing treatment-resistant symptoms of depression," *Games for health journal*, vol. 8, no. 5, pp. 332–338, 2019.
- [369] C. V. Russoniello, K. O'Brien, and J. M. Parks, "The effectiveness of casual video games in improving mood and decreasing stress," *Journal of CyberTherapy & Rehabilitation*, vol. 2, no. 1, pp. 53–66, 2009.
- [370] S. Safdar, W. Friedlmeier, D. Matsumoto, S. H. Yoo, C. T. Kwantes, H. Kakai, and E. Shigemasu, "Variations of emotional display rules within and across cultures: A comparison between canada, usa, and japan." *Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement*, vol. 41, no. 1, p. 1, 2009.
- [371] A. Samal and P. A. Iyengar, "Automatic recognition and analysis of human faces and facial expressions: A survey," *Pattern recognition*, vol. 25, no. 1, pp. 65–77, 1992.
- [372] E. Samuels and E. Szabadi, "Functional neuroanatomy of the noradrenergic locus coeruleus: its roles in the regulation of arousal and autonomic function part ii: physiological and pharmacological manipulations and pathological alterations of locus coeruleus activity in humans," *Current neuropharmacology*, vol. 6, no. 3, pp. 254–285, 2008.
- [373] A. Sanchez-Comas, K. Synnes, D. Molina-Estren, A. Troncoso-Palacio, and Z. Comas-González, "Correlation analysis of different measurement places of galvanic skin response in test groups facing pleasant and unpleasant stimuli," *Sensors*, vol. 21, no. 12, p. 4210, 2021.
- [374] M. Sarchiapone, C. Gramaglia, M. Iosue, V. Carli, L. Mandelli, A. Serretti, D. Marangon, and P. Zeppegno, "The association between electrodermal

- activity (eda), depression and suicidal behaviour: A systematic review and narrative synthesis," *BMC psychiatry*, vol. 18, no. 1, p. 22, 2018.
- [375] G. Sartori, R. Job, P. Tressoldi *et al.*, "Dde-2, batteria per la valutazione della dislessia e della disortografia evolutiva-2." 2007.
- [376] G. Sartori, R. Job, and P. E. Tressoldi, *Batteria per la valutazione della dislessia e della disortografia evolutiva: manuale*. Organizzazioni Speciali, 1995.
- [377] T. Sato, "Development of the japanese version of positive and negative affect schedule (panas) scales," *Japanese Journal of Personality*, vol. 9, p. 138, 2001.
- [378] W. Sato, T. Kochiyama, and S. Yoshikawa, "Physiological correlates of subjective emotional valence and arousal dynamics while viewing films," *Biological Psychology*, vol. 157, p. 107974, 2020.
- [379] K. G. Saulnier, M. Volarov, and N. P. Allan, "Anxiety sensitivity social concerns predicts electrodermal activity during the niacin biological challenge paradigm," *Psychiatry International*, vol. 3, no. 4, pp. 336–345, 2022.
- [380] S. Schachter and J. Singer, "Cognitive, social, and physiological determinants of emotional state," *Psychological review*, vol. 69, no. 5, p. 379, 1962.
- [381] S. A. Schapkin, J. Ragatz, M. Hillmert, and P. D. Gajewski, "Cognitive load and task engagement assessed with eeg spectral power during multiple object tracking," *Biological Psychology*, vol. 154, p. 107924, 2020.
- [382] M. Schmidt, M. Schels, and F. Schwenker, "A hidden markov model based approach for facial expression recognition in image sequences," in *IAPR workshop on artificial neural networks in pattern recognition*. Springer, 2010, pp. 149–160.
- [383] N. B. Schmidt, J. A. Richey, M. J. Zvolensky, and J. K. Maner, "Exploring human freeze responses to a threat stressor," *Journal of behavior therapy and experimental psychiatry*, vol. 39, no. 3, pp. 292–304, 2008.
- [384] E. F. Schneider, A. Lang, M. Shin, and S. D. Bradley, "Death with a story: How story impacts emotional, motivational, and physiological responses to first-person shooter video games," *Human communication research*, vol. 30, no. 3, pp. 361–375, 2004.
- [385] C. Schrader and T. Bastiaens, "Computer games and learning: The relationship between design, gameplay and outcomes," *Journal of Interactive Learning Research*, vol. 23, no. 3, pp. 251–271, 2012.
- [386] B. Schuller, G. Rigoll, and M. Lang, "Hidden markov model-based speech emotion recognition," in *2003 IEEE International Conference on Acoustics*,

- Speech, and Signal Processing, 2003. Proceedings.(ICASSP'03).*, vol. 2. Ieee, 2003, pp. II–1.
- [387] L. Schwartz, J. Levy, Y. Shapira, C. Salomonski, O. Hayut, O. Zagoory-Sharon, and R. Feldman, “Empathy aligns brains in synchrony,” *iScience*, vol. 28, no. 6, 2025.
 - [388] S. R. Schweinberger, E. C. Pickering, I. Jentzsch, A. M. Burton, and J. M. Kaufmann, “Event-related brain potential evidence for a response of inferior temporal cortex to familiar face repetitions,” *Cognitive Brain Research*, vol. 14, no. 3, pp. 398–409, 2002.
 - [389] H. Sedghamiz, ““complete pan tompkins implementation ecg qrs detector.” matlab central file exchange. [online],” <https://it.mathworks.com/matlabcentral/fileexchange/45840-complete-pan-tompkins-implementation-ecg-qrs-detector>, accessed: 21-Feb-2026.
 - [390] —, “Matlab implementation of pan tompkins ecg qrs detector,” *Code Available at the File Exchange Site of MathWorks*, pp. 1–3, 2014.
 - [391] Y. S. Seo, “Individualism, collectivism, client expression, and counselor effectiveness among south korean international students,” *The Counseling Psychologist*, vol. 38, no. 6, pp. 824–847, 2010.
 - [392] J. Sergent, S. Ohta, and B. Macdonald, “Functional neuroanatomy of face and object processing: a positron emission tomography study,” *Brain*, vol. 115, no. 1, pp. 15–36, 1992.
 - [393] M. R. Short, J. C. Hernandez-Pavon, A. Jones, and J. L. Pons, “Eeg hyper-scanning in motor rehabilitation: a position paper,” *Journal of neuroengineering and rehabilitation*, vol. 18, no. 1, p. 98, 2021.
 - [394] N. Shourie, M. Firoozabadi, and K. Badie, “Analysis of eeg signals related to artists and nonartists during visual perception, mental imagery, and rest using approximate entropy,” *BioMed research international*, vol. 2014, no. 1, p. 764382, 2014.
 - [395] L. Shu, J. Xie, M. Yang, Z. Li, Z. Li, D. Liao, X. Xu, and X. Yang, “A review of emotion recognition using physiological signals,” *Sensors*, vol. 18, no. 7, p. 2074, 2018.
 - [396] E. H. Siegel, M. K. Sands, W. Van den Noortgate, P. Condon, Y. Chang, J. Dy, K. S. Quigley, and L. F. Barrett, “Emotion fingerprints or emotion populations? a meta-analytic investigation of autonomic features of emotion categories,” *Psychological bulletin*, vol. 144, no. 4, p. 343, 2018.
 - [397] J. Simpson, S. Carter, S. H. Anthony, and P. G. Overton, “Is disgust a homogeneous emotion?” *Motivation and emotion*, vol. 30, pp. 31–41, 2006.

- [398] D. J. A. Smit, W. B. Gunning, D. F. Swaab, M. W. van der Molen, and F. M. van der Veen, "Alpha and beta power in the eeg during creative ideation as a function of task modality," *Biological Psychology*, vol. 69, no. 1, pp. 126–134, 2005.
- [399] W. Sommer, K. Stapor, G. Kończak, K. Kotowski, P. Fabian, J. Ochab, A. Bereś, and G. Ślusarczyk, "The n250 event-related potential as an index of face familiarity: a replication study," *Royal Society Open Science*, vol. 8, no. 6, p. 202356, 2021.
- [400] C. J. Stam, G. Nolte, and A. Daffertshofer, "Phase lag index: assessment of functional connectivity from multi channel eeg and meg with diminished bias from common sources," *Human brain mapping*, vol. 28, no. 11, pp. 1178–1193, 2007.
- [401] A. Stein, Y. Yotam, R. Puzis, G. Shani, and M. Taieb-Maimon, "Eeg-triggered dynamic difficulty adjustment for multiplayer games," *Entertainment computing*, vol. 25, pp. 14–25, 2018.
- [402] S. R. Steinhauer, G. J. Siegle, R. Condray, and M. Pless, "Sympathetic and parasympathetic innervation of pupillary dilation during sustained processing," *International journal of psychophysiology*, vol. 52, no. 1, pp. 77–86, 2004.
- [403] M. Stojanovic, "Gamer demographics: The definitive guide," 2024, accessed: 2024-08-01. [Online]. Available: <https://playtoday.co/blog/stats/gamer-demographics/>
- [404] G. P. Strauss, F. Z. Esfahlani, I. M. Rough, L. Luther, and H. Sayama, "Markov chain analysis indicates that positive and negative emotions have abnormal temporal interactions during daily life in schizophrenia," *Journal of Psychiatric Research*, vol. 164, pp. 344–349, 2023.
- [405] A. Strawhacker, A. Sullivan, C. Verish, M. U. Bers, and O. Shaer, "Enhancing children's interest and knowledge in bioengineering through an interactive videogame," *Journal of Information Technology Education. Innovations in Practice*, vol. 17, p. 55, 2018.
- [406] W. Struckmann, R. Bodén, M. Gingnell, D. Fällmar, and J. Persson, "Modulation of dorsolateral prefrontal cortex functional connectivity after intermittent theta-burst stimulation in depression: combining findings from fnirs and fmri," *NeuroImage: Clinical*, vol. 34, p. 103028, 2022.
- [407] S. Studio, "Grove - gsr sensor," 2025, accessed: 2025-01-08. [Online]. Available: <https://wiki.seedstudio.com/Grove-GSR.Sensor/>
- [408] I. S. Suhaili, Z. Nagy, and Z. Juhasz, "Functional connectivity differences in the perception of abstract and figurative paintings," *Applied Sciences*, vol. 14, no. 20, p. 9284, 2024.

- [409] N. S. Suhaimi, J. Mountstephens, and J. Teo, "Eeg-based emotion recognition: a state-of-the-art review of current trends and opportunities," *Computational intelligence and neuroscience*, vol. 2020, no. 1, p. 8875426, 2020.
- [410] Y. Sung and S. F. Tinkham, "Brand personality structures in the united states and korea: Common and culture-specific factors," *Journal of consumer psychology*, vol. 15, no. 4, pp. 334–350, 2005.
- [411] E. Szabadi, "Functional neuroanatomy of the central noradrenergic system," *Journal of psychopharmacology*, vol. 27, no. 8, pp. 659–693, 2013.
- [412] R. Szeliski, *Computer vision: algorithms and applications*. Springer Nature, 2022.
- [413] J. Sztajzel, "Heart rate variability: a noninvasive electrocardiographic method to measure the autonomic nervous system," *Swiss medical weekly*, vol. 134, no. 3536, pp. 514–522, 2004.
- [414] K. Tae-Young, "Motivation and attitudes toward foreign language learning as socio-politically mediated constructs: The case of korean high school students," *Journal of Asia TEFL*, vol. 3, no. 2, 2006.
- [415] M. Tahlir, A. M. Miron, and F. H. Rauscher, "Music choice as a sadness regulation strategy for resolved versus unresolved sad events," *Psychology of Music*, vol. 41, no. 6, pp. 729–748, 2013.
- [416] F. Takens, "Detecting strange attractors in turbulence," in *Dynamical Systems and Turbulence, Warwick 1980: proceedings of a symposium held at the University of Warwick 1979/80*. Springer, 2006, pp. 366–381.
- [417] N. Takeuchi, "A dual-brain therapeutic approach using noninvasive brain stimulation based on two-person neuroscience: A perspective review," *Mathematical Biosciences and Engineering*, vol. 21, no. 4, pp. 5118–5137, 2024.
- [418] P. Tambe, P. Cappelli, and V. Yakubovich, "Artificial intelligence in human resources management: Challenges and a path forward," *California Management Review*, vol. 61, no. 4, pp. 15–42, 2019.
- [419] H. Tang, X. Mai, S. Wang, C. Zhu, F. Krueger, and C. Liu, "Interpersonal brain synchronization in the right temporo-parietal junction during face-to-face economic exchange," *Social cognitive and affective neuroscience*, vol. 11, no. 1, pp. 23–32, 2016.
- [420] R. Tang, L. De Donato, N. Besinović, F. Flammini, R. M. Goverde, Z. Lin, R. Liu, T. Tang, V. Vittorini, and Z. Wang, "A literature review of artificial intelligence applications in railway systems," *Transportation Research Part C: Emerging Technologies*, vol. 140, p. 103679, 2022.
- [421] C. Tappolet and M. Rossi, "Emotions and wellbeing," *Topoi*, vol. 34, pp. 461–474, 2015.

- [422] P. Tarchi, F. Calà, L. Frassinetti, and A. Lanatà, "Event-related potentials in complex and simple words-pseudowords aloud reading task," in *2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2024, pp. 1–4.
- [423] P. Tarchi, L. Frassinetti, G. Faralli, F. Cala, M. C. Lanini, and A. Lanata, "Quantitative electrodermal activity analysis of simultaneous recordings from dyads during affective visual task: Proof of concept and preliminary results," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, vol. 2025, 2025, pp. 1–6.
- [424] P. Tarchi, M. C. Lanini, L. Frassinetti, and A. Lanatà, "Real and deepfake face recognition: An eeg study on cognitive and emotive implications," *Brain Sciences*, vol. 13, no. 9, p. 1233, 2023.
- [425] J.-P. Tauscher, S. Castillo, S. Bosse, and M. Magnor, "Eeg-based analysis of the impact of familiarity in the perception of deepfake videos," in *2021 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2021, pp. 160–164.
- [426] A. Tcherkassof and D. Dupré, "The emotion–facial expression link: evidence from human and automatic expression recognition," *Psychological research*, vol. 85, no. 8, pp. 2954–2969, 2021.
- [427] A. Terraciano, R. R. McCrae, and P. T. Costa Jr, "Factorial and construct validity of the italian positive and negative affect schedule (panas)." *Eur J Psychol Assess*, vol. 19, no. 2, p. 131, 2003.
- [428] H. Thadeshwar, V. Shah, M. Jain, R. Chaudhari, and V. Badgujar, "Artificial intelligence based self-driving car," in *2020 4th International Conference on Computer, Communication and Signal Processing (ICCCSP)*. IEEE, 2020, pp. 1–5.
- [429] J. F. Thayer and R. D. Lane, "A model of neurovisceral integration in emotion regulation and dysregulation," *Journal of affective disorders*, vol. 61, no. 3, pp. 201–216, 2000.
- [430] TMSiArtinis. (2024) Matlab interface for tmsi systems. Accessed: 2024-03-08. [Online]. Available: <https://www.tmsi.artinis.com/matlab>
- [431] C. Tronstad, M. Amini, D. R. Bach, and Ø. G. Martinsen, "Current trends and opportunities in the methodology of electrodermal activity measurement," *Physiological measurement*, vol. 43, no. 2, p. 02TR01, 2022.
- [432] V. Vachiratamporn, R. Legaspi, K. Moriyama, K.-i. Fukui, and M. Numao, "An analysis of player affect transitions in survival horror games," *Journal on Multimodal User Interfaces*, vol. 9, no. 1, pp. 43–54, 2015.

- [433] G. Valenza, L. Citi, A. Lanatá, E. P. Scilingo, and R. Barbieri, “Revealing real-time emotional responses: a personalized assessment based on heartbeat dynamics,” *Scientific reports*, vol. 4, no. 1, p. 4998, 2014.
- [434] D. Van Der Mee, M. Gevonden, J. H. Westerink, and E. De Geus, “Validity of electrodermal activity-based measures of sympathetic nervous system activity from a wrist-worn device,” *International Journal of Psychophysiology*, vol. 168, pp. 52–64, 2021.
- [435] W. Van Drongelen, *Signal processing for neuroscientists*. Academic press, 2018.
- [436] L. C. M. Vanderlei, C. M. Pastre, R. A. Hoshi, T. D. d. Carvalho, and M. F. d. Godoy, “Noções básicas de variabilidade da frequência cardíaca e sua aplicabilidade clínica,” *Brazilian Journal of Cardiovascular Surgery*, vol. 24, pp. 205–217, 2009.
- [437] M. E. Vanutelli, L. Gatti, L. Angioletti, and M. Balconi, “Affective synchrony and autonomic coupling during cooperation: a hyperscanning study,” *BioMed Research International*, vol. 2017, no. 1, p. 3104564, 2017.
- [438] R. Veerabhadrapa, I. T. Hettiarachchi, and A. Bhatti, “Using recurrence quantification analysis to quantify the physiological synchrony in dyadic ecg data,” in *2021 IEEE International Systems Conference (SysCon)*. IEEE, 2021, pp. 1–8.
- [439] Y. R. Veeranki, N. Ganapathy, R. Swaminathan, and H. F. P. Quintero, “Comparison of electrodermal activity signal decomposition techniques for emotion recognition,” *IEEE Access*, 2024.
- [440] C. Ventura-Bort, J. Wendt, and M. Weymar, “New insights on the correspondence between subjective affective experience and physiological responses from representational similarity analysis,” *Psychophysiology*, vol. 59, no. 11, p. e14088, 2022.
- [441] M. Vinck, R. Oostenveld, M. Van Wingerden, F. Battaglia, and C. M. Pennartz, “An improved index of phase-synchronization for electrophysiological data in the presence of volume-conduction, noise and sample-size bias,” *Neuroimage*, vol. 55, no. 4, pp. 1548–1565, 2011.
- [442] A. Vourvopoulos, S. Bermudez i Badia, and F. Liarokapis, “Eeg correlates of video game experience and user profile in motor-imagery-based brain-computer interaction,” *The Visual Computer*, vol. 33, pp. 533–546, 2017.
- [443] M. Vuorre, N. Johannes, K. Magnusson, and A. K. Przybylski, “Time spent playing video games is unlikely to impact well-being,” *R Soc Open Sci*, vol. 9, no. 7, p. 220411, 2022.

- [444] I. F. Wallace, N. D. Berkman, L. R. Watson, T. Coyne-Beasley, C. T. Wood, K. Cullen, and K. N. Lohr, "Screening for speech and language delay in children 5 years old and younger: a systematic review," *Pediatrics*, vol. 136, no. 2, pp. e448–e462, 2015.
- [445] B. Walsh and E. Usler, "Physiological correlates of fluent and stuttered speech production in preschool children who stutter," *Journal of Speech, Language, and Hearing Research*, vol. 62, no. 12, pp. 4309–4323, 2019.
- [446] S.-M. Wang, D. W. Kang, Y. H. Um, S. Kim, S. Lee, C. U. Lee, and H. K. Lim, "Effects of serious games in older adults with mild cognitive impairment," *Psychiatry Investigation*, vol. 21, no. 5, p. 449, 2024.
- [447] Y. Wang, Y. Li, Y. Song, and X. Rong, "Facial expression recognition based on random forest and convolutional neural network," *Information*, vol. 10, no. 12, p. 375, 2019.
- [448] D. Watson, L. A. Clark, and A. Tellegen, "Development and validation of brief measures of positive and negative affect: the panas scales." *Journal of personality and social psychology*, vol. 54, no. 6, p. 1063, 1988.
- [449] W. Westera, "Simulating serious games: a discrete-time computational model based on cognitive flow theory," *Interactive Learning Environments*, vol. 26, no. 4, pp. 539–552, 2018.
- [450] J. B. Wilmer, L. Germine, C. F. Chabris, G. Chatterjee, M. Williams, E. Loken, K. Nakayama, and B. Duchaine, "Human face recognition ability is specific and highly heritable," *Proceedings of the National Academy of sciences*, vol. 107, no. 11, pp. 5238–5241, 2010.
- [451] G. V. Wilson and J. H. Kerr, "Affective responses to success and failure:: a study of winning and losing in competitive rugby," *Personality and Individual Differences*, vol. 27, no. 1, pp. 85–99, 1999.
- [452] K. A. Wilson, G. A. James, C. D. Kilts, and K. A. Bush, "Combining physiological and neuroimaging measures to predict affect processing induced by affectively valent image stimuli," *Scientific Reports*, vol. 10, no. 1, p. 9298, 2020.
- [453] I. Winkler, S. Haufe, and M. Tangermann, "Automatic classification of artifactual ica-components for artifact removal in eeg signals," *Behavioral and brain functions*, vol. 7, no. 1, p. 30, 2011.
- [454] T. Wollmann, F. Abtahi, A. Eghdam, F. Seoane, K. Lindecrantz, M. Haag, and S. Koch, "User-centred design and usability evaluation of a heart rate variability biofeedback game," *IEEE Access*, vol. 4, pp. 5531–5539, 2016.
- [455] S. Xu, J. Wang, W. Shou, T. Ngo, A.-M. Sadick, and X. Wang, "Computer vision techniques in construction: a critical review," *Archives of Computational Methods in Engineering*, vol. 28, pp. 3383–3397, 2021.

- [456] G. N. Yannakakis, H. P. Martínez, and A. Jhala, “Towards affective camera control in games,” *User Modeling and User-Adapted Interaction*, vol. 20, no. 4, pp. 313–340, 2010.
- [457] G. N. Yannakakis and D. Melhart, “Affective game computing: A survey,” *Proceedings of the IEEE*, vol. 111, no. 10, pp. 1423–1444, 2023.
- [458] G. N. Yannakakis and J. Togelius, “Experience-driven procedural content generation,” *IEEE Transactions on Affective Computing*, vol. 2, no. 3, pp. 147–161, 2011.
- [459] Y.-c. Yeh, S. C. Lai, and C.-W. Lin, “The dynamic influence of emotions on game-based creativity: An integrated analysis of emotional valence, activation strength, and regulation focus,” *Computers in Human Behavior*, vol. 55, pp. 817–825, 2016.
- [460] M. Yeo, S. Lim, and G. Yoon, “Analysis of biosignals during immersion in computer games,” *Journal of Medical Systems*, vol. 42, pp. 1–9, 2018.
- [461] Y. You, A. Correias, D. R. White, L. C. Wagner, R. J. J. Keehn, B. Q. Rosen, K. Alemu, R.-A. Müller, and K. Marinkovic, “Mapping access to meaning in adolescents with autism: Atypical lateralization and spatiotemporal patterns as a function of language ability,” *NeuroImage: Clinical*, vol. 39, p. 103467, 2023.
- [462] H. Yu, M. Xu, X. Xiao, F. Xu, and D. Ming, “Detection of dynamic changes of electrodermal activity to predict the classroom performance of college students,” *Cognitive Neurodynamics*, vol. 18, no. 1, pp. 173–184, 2024.
- [463] K.-H. Yu, A. L. Beam, and I. S. Kohane, “Artificial intelligence in health-care,” *Nature biomedical engineering*, vol. 2, no. 10, pp. 719–731, 2018.
- [464] K. Yun, K. Watanabe, and S. Shimojo, “Interpersonal body and neural synchronization as a marker of implicit social interaction,” *Scientific reports*, vol. 2, no. 1, p. 959, 2012.
- [465] A. Zamm, C. Palmer, A.-K. R. Bauer, M. G. Bleichner, A. P. Demos, and S. Debener, “Behavioral and neural dynamics of interpersonal synchrony between performing musicians: a wireless eeg hyperscanning study,” *Frontiers in Human Neuroscience*, vol. 15, p. 717810, 2021.
- [466] S. Zeki, “La visione dall’interno,” *Arte e cervello*, 2003.
- [467] —, *Con gli occhi del cervello: Immagini, luci, colori*. Di Renzo Editore, 2008.
- [468] X. Zhang and Y. Wang, “Exploring emotional and cognitive engagement during playing a serious game: using eeg and interview data,” in *Proceedings of the Twelfth International Symposium of Chinese CHI*, 2024, pp. 519–527.

- [469] L. Zheng, X. Li, and S. Wang, "Serious games and their effect improving attention in students with learning disabilities," *Computers & Education*, vol. 136, pp. 43–61, 2019.
- [470] X. Zhou and P. C. Wong, "Hyperscanning to explore social interaction among autistic minds," *Neuroscience & Biobehavioral Reviews*, vol. 163, p. 105773, 2024.
- [471] M. Zohaib, "Dynamic difficulty adjustment (dda) in computer games: A review," *Advances in Human-Computer Interaction*, vol. 2018, no. 1, p. 5681652, 2018.

La borsa di dottorato è stata finanziata con risorse dell'Unione europea-*NextGeneration EU*
Piano Nazionale di Ripresa e Resilienza Missione 4 – Componente 2 – “Dalla ricerca all’impresa” –
Investimento “AGE-IT – Ageing well in an ageing society” – *CUP B83C22004800006*