Technical Research Statement

This Technical Research Statement outlines the methodological foundations, experimental designs, and modeling architectures developed throughout my research in AI for Health, with a focus on neural decoding and multimodal biomedical modeling.

1) Early Foundations in Experimental and Computational Modeling

My master's training was centered on rigorous experimental design and quantitative modeling methodologies. Through laboratory-intensive activities, I developed expertise in planning, programming, executing, and statistically validating experimental paradigms across clinical, cognitive, social, and neuroscientific domains.

This training involved the systematic application of advanced quantitative and psychometric methods to formalize complex behavioral constructs into measurable variables. I worked with experimental software environments (i.e., E-Prime, Inquisit, Qualtrics) and statistical platforms (R, Jamovi) to design structured data acquisition pipelines and to validate multidimensional psychological models.

In parallel, I was introduced to scientific computing environments (MATLAB, R) for the data-driven validation and simulation of established psychological models (i.e., Rescorla-Wagner, Posner Task, Stroop Effect, Baddley) targeting reinforcement learning principles, attentional control tasks and memory modelling frameworks. These computational labs required implementing script-based simulations of experimental paradigms, enabling the comparison between theoretical model predictions and observed behavioral data. This exposure marked my first formal engagement with computational modeling as a methodological tool for hypothesis testing.

An additional component of this training focused on longitudinal and real-time data collection frameworks, including ecological momentary assessment (EMA) and ambulatory psychophysiological monitoring. These approaches required repeated sampling of behavioral, cognitive, and physiological signals through remote sensing devices and structured self-report tools. The objective was to model micro-processes underlying daily behavioral transitions, symptom progression, and treatment outcomes, thereby extracting short-range prognostic features from temporally structured data. This early methodological formation established the foundations of my computational mindset: treating behavioral and psychological phenomena as structured, measurable, and modellable dynamical processes.

2) Interdisciplinary Research Experience in Neurotechnology and Interactive Systems

Human–Technology Interaction and Sensory Augmentation (IIT – Robotics and Brain Cognitive Sciences Unit)

At the Italian Institute of Technology (IIT), within the Robotics and Brain Cognitive Sciences Unit, I contributed to the prototype evaluation of a sensory-augmentation wearable device ("Glassense"), designed to enhance speech perception in noisy environments through spatial acoustic filtering.

This project exposed me to the modeling of human perceptual systems under altered sensory conditions. The core challenge involved evaluating how artificial sensory transformations interact with neural and cognitive processing mechanisms. This experience strengthened my understanding of embodied information processing systems, where technology interfaces directly with human perceptual dynamics.

VR-Based Neuroergonomic Modeling for Parkinson's Disease (AIS Lab – University of Milan)

At the Applied Intelligent Systems Laboratory (AIS Lab) of Professor Alessandro Borghese, at the Computer Science Department of the University of Milan, in collaboration with a clinical hospital setting (ASST Santi Paolo and Carlo), I worked on the design and validation of immersive virtual reality (VR) paradigms for the study of cognitive-motor impairments in Parkinson's disease.

The project focused on modeling the phenomenon of "freezing of gait" (FOG) within controlled virtual environments. The methodological objective was to manipulate spatial and perceptual affordances in the digital environment and quantify their effects on motor planning and prediction mechanisms.

Rather than treating VR as a visualization tool, we approached it as an experimental modeling platform capable of systematically perturbing perception–action coupling mechanisms. Sensory manipulations (i.e., alterations in spatial dimensions or environmental constraints) were introduced to test their influence on motor prediction errors and locomotion dynamics.

My role involved optimizing the ecological validity of these simulations using cognitive ergonomics principles, including:

- perceptual fidelity of simulated sensory signals
- multisensory integration consistency
- predictability and feedback alignment with motor expectations

This required close collaboration with engineers and developers to align computational rendering choices (Unity-based implementation) with experimentally controlled variables.
From a modeling perspective, this experience marked a shift toward the study of embodied dynamical systems, where brain, body, and environment form an interactive loop. It also reinforced my interest in integrating signal processing, computational modeling, and interactive technologies to investigate and potentially modulate pathological neural mechanisms.

Methodological Impact
These interdisciplinary research experiences consolidated my transition toward computational neuroscience and AI. They demonstrated how sensor-based systems, immersive technologies, and algorithmic modeling could converge within a unified framework for studying complex biological processes under controlled perturbations.
Crucially, they strengthened my orientation toward building experimental systems that do not merely measure behavior, but actively manipulate and model the underlying computational principles governing perception, action, and neural prediction.

3) Formal Training in Artificial Intelligence and Multi-Scale Computational Modeling
Following my interdisciplinary research experiences in neurotechnology and interactive systems, I pursued structured training in machine learning and artificial intelligence to consolidate and formalize my computational approach.
In parallel with my research activities, I developed practical competencies in data science and deep learning using Python-based frameworks, focusing on representation learning, optimization, and signal modeling techniques applicable to high-dimensional behavioral and neural datasets.

AI-DLDA Summer School (University of Udine)
I was awarded a competitive scholarship to attend the International AI-DLDA Summer School, where I presented a white paper exploring how computational models of Peripersonal Space and embodied cognition could inform AI-driven sensing systems for large-scale public health interventions (i.e., prevention of pandemic spread during COVID-19 crisis)
The program combined theoretical lectures and practical coding sessions covering topics such as computer vision, explainable AI, robotics, cybersecurity, and behavioral analytics. Exposure to these domains reinforced the scalability of AI methodologies across heterogeneous application areas and strengthened my understanding of AI as a unifying computational paradigm.
Importantly, this experience marked a conceptual shift from task-specific modeling toward scalable architectures capable of generalization across domains.

AS-AI School – Italian National Research Council (ISTC-CNR)
To deepen this transition, I enrolled in the Advanced School in Artificial Intelligence (AS-AI) at ISTC-CNR. The program provided rigorous training in machine learning, deep learning, reinforcement learning, and computational modeling of brain–behavior relationships across abstraction levels.
The curriculum covered both applied AI domains (computer vision, natural language processing, knowledge representation, reinforcement learning) and multi-scale computational neuroscience models (from single-neuron dynamics to probabilistic and connectionist frameworks). This dual exposure strengthened my ability to reason across levels of biological and computational abstraction.
As part of the program, I completed a six-month research training focused on EEG-based decoding of motor intention using deep neural networks. This project required implementing and validating end-to-end pipelines for neural signal preprocessing, feature extraction, and classification within a brain–computer interface framework.

From a methodological standpoint, this experience consolidated several core competencies:

- optimization of neural network architectures for structured biomedical signals
- handling limited-sample, high-dimensional datasets
- integration of signal processing and representation learning
- translation of computational models into clinically relevant applications

Methodological Consolidation

This phase of formal AI training did not represent a departure from my earlier trajectory, but rather its structural consolidation. It allowed me to unify experimental neuroscience, human–technology interaction, and signal processing within scalable machine learning frameworks.

Rather than approaching AI as a tool added on top of a previous background, I progressively integrated it as the central modeling language through which brain, behavior, and interaction systems could be analyzed and simulated.

This consolidation naturally led to my PhD in Artificial Intelligence (Health & Life Sciences track), where I further developed AI-driven methodologies for decoding neural and socio-affective processes and began extending these approaches toward system-level, multimodal biomedical modeling.

4) Doctoral Research: AI-Driven Neural Decoding and Multimodal System-Level Modeling

During my PhD in Artificial Intelligence (Health & Life Sciences track), I have focused on developing AI-based methodologies for decoding and modeling high-dimensional neural dynamics from electroencephalographic (EEG) data. My research spans two complementary directions: (i) neural decoding for brain–computer interface (BCI) applications, and (ii) system-level modeling of socio-affective processes using hyperscanning paradigms.

Neural Decoding and Explainable Deep Learning for Brain–Computer Interfaces

My initial doctoral work centered on the development of automated and explainable AI pipelines for decoding motor execution and motor imagery states from EEG recordings. I implemented end-to-end workflows including:

- signal preprocessing and artifact correction
- time-domain and time–frequency feature extraction (wavelet-based representations)
- 1D and 2D input reformulations (raw signals and spectrogram maps)
- classical machine learning models (Logistic Regression, SVM, XGBoost)
- deep learning architectures (CNN2D, BiLSTM, Transformers, hybrid CNN–LSTM, Separable and 3D CNNs)

To enhance interpretability, I integrated explainability techniques (i.e., Grad-CAM) for identifying the spatiotemporal and spectral contributions driving model decisions. This enabled retrospective analysis of frequency-specific and region-specific (sensor-level) neural dynamics associated with motor intention. From a methodological standpoint, this work addressed several challenges characteristic of biomedical AI:

- high-dimensional, low-sample-size regimes
- structured temporal dependencies
- inter-subject variability
- interpretability constraints in clinical contexts

Hyperscanning and Socio-Affective Neural Modeling

My second doctoral line of research extended neural decoding into social interaction settings using EEG hyperscanning, where two participants' brain signals are recorded simultaneously during interactive tasks (i.e., two-person neuroscience). Although hyperscanning enables the study of inter-brain dynamics, my primary methodological focus was on single-trial decoding of event-related potentials (ERPs), particularly the P300 component, within socio-affective decision-making paradigms.

I contributed to the design and validation of a hyperscanning protocol implemented in a randomized clinical trial context, aimed at investigating socio-affective evaluation processes during interactive tasks. The computational objective was to determine whether P300-related neural responses—an index of evaluative and motivational processing—could be reliably decoded at the single-trial level and whether their spectral dynamics varied as a function of interpersonal closeness (familiar vs unfamiliar dyads).

Methodologically, this involved:

- extracting ERPs at the single-trial level
- decomposing P300 responses into time–frequency representations (event-related oscillations; theta and delta bands)
- constructing feature maps from wavelet-based spectral decompositions
- implementing classical and deep learning classifiers for condition discrimination

The core research question was whether event-related spectral dynamics underlying the P300 carried discriminative information about responsibility attribution and empathic evaluation processes, and whether these features could generalize across dyadic interaction conditions.
This work reinforced the importance of modeling neural signals not only at the averaged ERP level, but within high-dimensional, temporally structured representations suitable for machine learning architectures.

Toward Multimodal and Multi-Scale Biomedical AI
Beyond task-specific decoding, my doctoral research progressively shifted toward broader system-level questions. Although hyperscanning enables the joint recording of interacting brains, it also reveals methodological limitations in approaches that rely solely on pairwise neural correlations while neglecting embodied behavioral signals exchanged between agents (i.e., Computational Embodied Social Neuroscience [i; ii]).
This highlights the need for multimodal modeling strategies integrating:

- neural dynamics
- behavioral and biometric signals (gesture, facial expression, gaze, vocal prosody)
- longitudinal contextual data

From a computational standpoint, this implies moving toward synchronized multimodal streamed data, where brain and body signals are treated as coupled observational levels (i.e., "behaviorally-meaningful windows of interest") within a unified modeling framework. In such a setting, synchronization patterns are understood as emergent properties of structured interactions across modalities rather than as isolated pairwise correlations. Dynamical System Theory provides a useful conceptual foundation for this shift, suggesting that behavior can emerge from non-linear coupling between brain, body, and environment. Translating this perspective into AI systems requires architectures capable of learning structured representations across interacting subsystems [iii; iv].

These challenges align with the broader transition in artificial intelligence toward multi-modal, multi-scale representation learning.

My work increasingly converges on the development of architectures capable of:

- modeling temporally structured, multimodal biomedical streams
- learning cross-level representations (neural–behavioral–physiological)
- integrating uncertainty-aware predictions
- scaling from localized biomarkers to longitudinal health trajectories

In this sense, my doctoral research represents a methodological bridge between neural signal decoding and large-scale biomedical modeling.
The transition from isolated biomarkers toward integrated system-level representations parallels ongoing developments in foundation models for health, where heterogeneous data modalities are embedded within scalable, shared representation spaces.
Overall, my research trajectory is centered on designing AI systems that move from localized neural decoding toward scalable, multimodal representations capable of modeling complex health-related phenomena across biological scales. I aim to contribute to the development of foundation-level architectures for biomedical data that integrate neural, behavioral, and physiological dynamics within unified computational frameworks.