Extended Research Background

Research Trajectory and System-Level Vision in AI for Health

My academic and research trajectory has been guided by a main underlying question: how can complex human systems – spanning brain, behavior, physiology, and social interaction – be formally modeled using computational frameworks? Although my formal training began in experimental psychology, I approached this discipline not as a purely descriptive science, but as the study of complex adaptive systems. Early exposure to experimental design, quantitative modeling, and computational simulations allowed me to formalize cognitive and behavioral constructs into measurable variables and structured analytical pipelines. Through statistical modeling, signal analysis, and early computational simulations of behavioral paradigms, I progressively developed a systems-oriented, data-driven mindset. Rather than treating psychological constructs as abstract entities, I learned to view them as dynamical processes that could be parameterized, modeled, and tested under computational constraints.

This perspective naturally led me toward artificial intelligence as a unifying methodological framework capable of scaling from behavioral dynamics to neural representations.

Neural Systems as High-Dimensional Testbeds

During my PhD in Artificial Intelligence (Health & Life Sciences track), neural systems became a high-dimensional testbed for developing scalable computational modeling strategies. I designed and validated AI-driven pipelines for single-trial decoding of neuromotor and socio-affective states from EEG data, employing convolutional, recurrent, and Transformer-based architectures, alongside explainability methods to interpret spatiotemporal and sensor-spectral contributions. Working with EEG hyperscanning data further extended this approach. In this setting, I found that interacting brains could be modeled not as isolated units, but as components of a coupled dynamical system. This required integrating spectral, temporal, and topological features within unified learning pipelines, while addressing inter-subject variability, limited sample size, and structured noise – conditions characteristic of real-world biomedical datasets –.

Through these projects, my trajectory has progressively positioned me not as an experimental psychologist who later adopted machine learning, but rather as a systems-level biopsychosocial modeler, who began from behavioral dynamics and moved toward neural representations, and who is now extending this framework toward scalable foundation models for health and life sciences. The core methodological challenge I have repeatedly encountered is the modeling of high-dimensional, temporally structured biomedical data under uncertainty. This computational modelling opportunities naturally motivates a transition from task-specific decoding models toward architectures capable of learning generalizable, cross-modal representations at scale.

Toward Large-Scale, Multi-Modal Biomedical Modeling

My work is progressively moving toward large-scale, multi-modal biomedical modeling, where heterogeneous signals – neural, physiological, behavioral, and potentially molecular or clinical – can be embedded into shared representation spaces. My long-term research direction is centered on developing AI architectures that bridge biological scales, from neural dynamics to behavioral phenotypes and longitudinal clinical trajectories. I aim to contribute to the design of models capable of:

- learning cross-modal representations across heterogeneous biomedical signals
- modeling longitudinal health trajectories under uncertainty
- integrating multi-scale data (micro to macro levels) within unified learning frameworks
- leveraging generative and foundation-model approaches to support prediction, simulation, and decision-making in healthcare contexts

In this perspective, foundation models for health represent not a departure from my current work, but its natural extension. The methodological principles underlying neural decoding – representation learning, temporal modeling, uncertainty handling, multimodal integration – are directly aligned with the challenges of large-scale biomedical AI. Beyond methodology, my background in human-centered research ensures that modeling decisions remain anchored to interpretability, clinical relevance, and real-world deployment constraints. I view scalable AI systems for health not merely as predictive tools, but as computational infrastructures that must integrate biological complexity while remaining actionable in practice.

For a detailed account of experimental designs, modeling architectures, and technical implementations, please refer to the accompanying "**Technical Research Statement**".