# Quantum Neuroinformatics for Multi-Modal Brain Imaging: Integrating fMRI,

EEG, and Genomic Data to Model Complex Neuropsychiatric Phenotypes

**Zeynep Alici**
University of Ottawa

***Abstract*—Advances in neuroimaging and genomics have enabled unprecedented insights into the biological underpinnings of neuropsychiatric disorders; however, integrating heterogeneous, high-dimensional datasets remains a significant analytical challenge. This paper explores quantum neuroinformatics for multi-modal brain imaging, focusing on the integration of functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and genomic data to model complex neuropsychiatric phenotypes. By leveraging hybrid quantum–classical machine learning frameworks, the study examines how quantum-enhanced feature mapping, probabilistic modeling, and high-dimensional optimization can improve the fusion and interpretation of multimodal datasets. The analysis evaluates the potential of quantum algorithms to capture nonlinear interactions across neural, temporal, and genetic domains, while also addressing computational and hardware limitations associated with the Noisy Intermediate-Scale Quantum (NISQ) era. The findings suggest that quantum neuroinformatics may offer a novel pathway for advancing precision psychiatry by enabling more accurate phenotypic classification, biomarker discovery, and personalized treatment strategies.**

The study of neuropsychiatric disorders has increasingly shifted toward data-intensive approaches that integrate information across multiple biological and temporal scales [9]. Disorders such as schizophrenia, depression, bipolar disorder, and autism spectrum conditions are characterized by complex interactions between neural activity, genetic predisposition, and environmental influences. Traditional single-modality analyses—focusing solely on brain imaging or genetic data—often fail to capture this multidimensional complexity [5]. As a result, there is growing interest in multimodal frameworks that combine functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and genomic data to develop more comprehensive models of brain function and dysfunction [1].

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Each of these modalities provides distinct yet complementary information. fMRI offers high spatial resolution, enabling the mapping of functional brain networks and regional activity patterns [13]. EEG provides high temporal resolution, capturing rapid neural dynamics and oscillatory activity. Genomic data contributes insights into the molecular and genetic architecture underlying neurobiological processes [6]. Integrating these modalities holds significant promise for advancing understanding of neuropsychiatric phenotypes; however, it also presents substantial computational and methodological

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challenges. Differences in data structure, scale, noise characteristics, and dimensionality complicate efforts to develop unified analytical models [12].

Machine learning and artificial intelligence have been widely applied to address these challenges, enabling pattern recognition, feature extraction, and predictive modeling in high-dimensional datasets. Nevertheless, classical machine learning approaches often encounter limitations when dealing with extremely large feature spaces, nonlinear dependencies, and complex interaction effects [7]. Multimodal neuroinformatics problems frequently involve combinatorial complexity that exceeds the efficient capabilities of traditional computational methods, particularly when attempting to model interactions across spatial, temporal, and genetic domains simultaneously [10].

Quantum computing introduces a novel computational paradigm that may enhance the analysis of such complex systems. By exploiting quantum mechanical principles such as superposition and entanglement, quantum algorithms can represent and process information in high-dimensional Hilbert spaces [4]. This capability offers theoretical advantages for feature mapping, probabilistic inference, and optimization in complex datasets. Hybrid quantum–classical models, which integrate quantum subroutines into classical machine learning pipelines, have emerged as practical approaches for leveraging these advantages within current hardware constraints [8].

In the context of neuroinformatics, quantum-enhanced models may facilitate more efficient integration of multimodal data by capturing higher-order correlations that are difficult to model using classical techniques. Quantum kernel methods, for example, enable the projection of data into complex feature spaces where patterns may become more separable [11]. Variational quantum circuits can be used to optimize model parameters in high-dimensional landscapes, potentially improving classification accuracy and predictive performance. These approaches align with the goals of precision psychiatry, which seeks to tailor diagnosis and treatment to individual biological profiles [3].

Despite these promising prospects, the application of quantum computing to neuroinformatics remains in its early stages. Hardware limitations, including qubit coherence, noise, and scalability constraints, restrict the complexity of implementable models [2]. Furthermore, the interpretability of quantum-enhanced models poses challenges for clinical translation, where transparency and explainability are essential. Ethical considerations, particularly related to the use of sensitive genetic and neurological data, also play a critical role in shaping research and application.

This paper investigates quantum neuroinformatics as a framework for integrating fMRI, EEG, and genomic data to model complex neuropsychiatric phenotypes. By examining hybrid computational architectures, methodological innovations, and practical limitations, the study aims to contribute to the development of more robust and scalable approaches to multimodal brain data analysis. Ultimately, the convergence of quantum computing and neuroinformatics represents a frontier in computational neuroscience, with the potential to transform how neuropsychiatric disorders are understood, diagnosed, and treated.

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