A Bi-directional Multimodal Generative model to Capture Visceral & Cerebral Dynamics

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Introduction & Motivation

Interoceptive rhythms such as the heartbeat are not noise, but structured signals that shape large-scale brain dynamics, perception, and self-related processing. Recent work suggests that brain–body interactions operate as a closed-loop system mediated by rhythmic synchronization and predictive mechanisms.

Goal: We propose a bi-directional generative framework that explicitly models brain–heart coupling as a dynamical system, enabling joint prediction and reconstruction of cerebral and visceral signals.

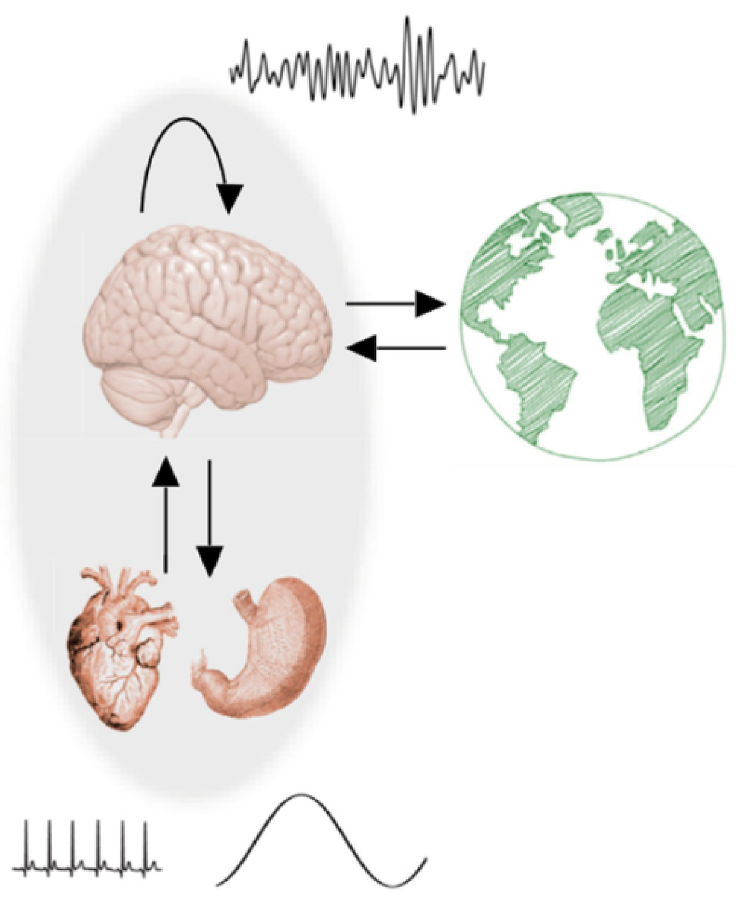
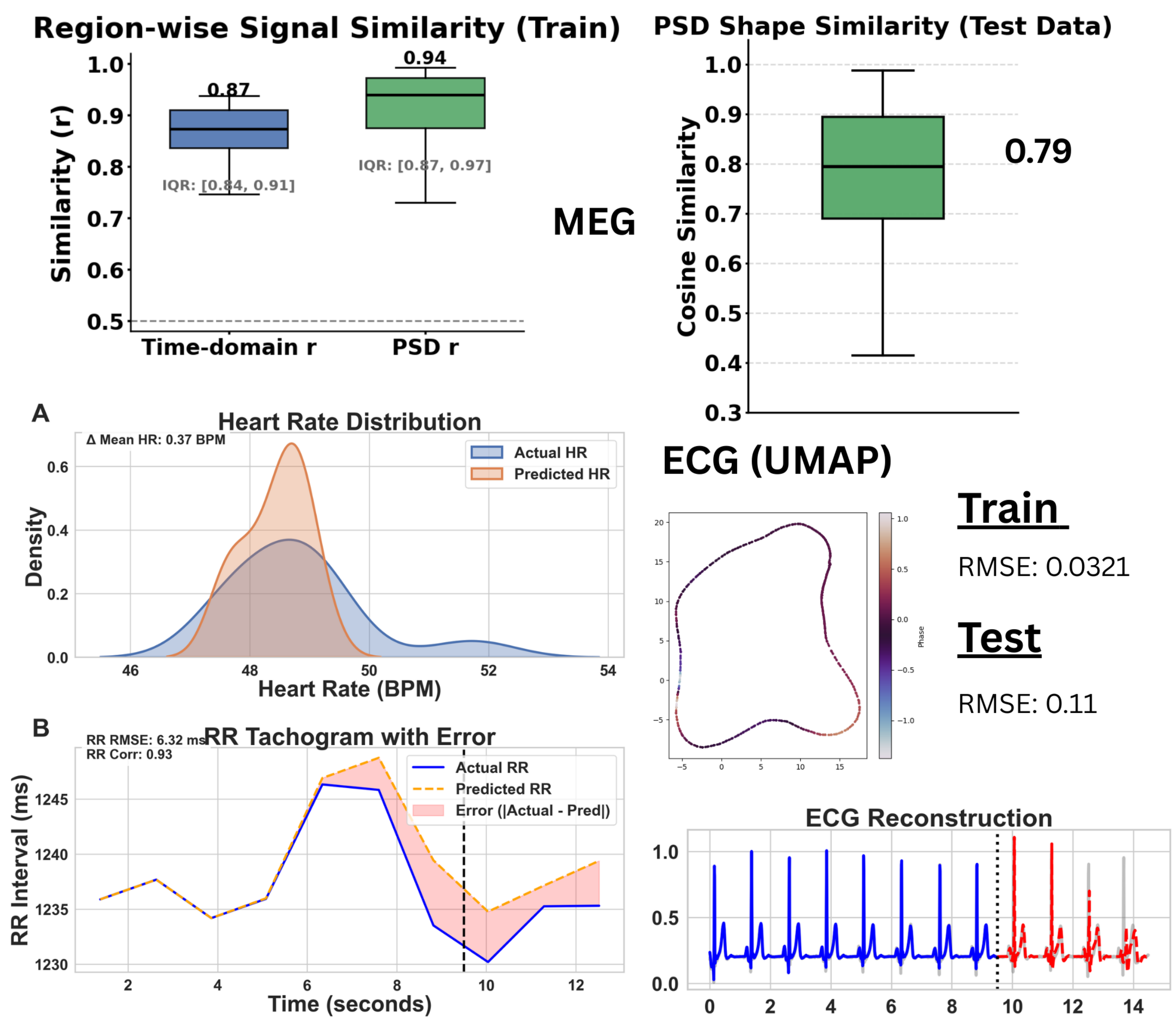


Figure 1:Catherene et al. (2019)

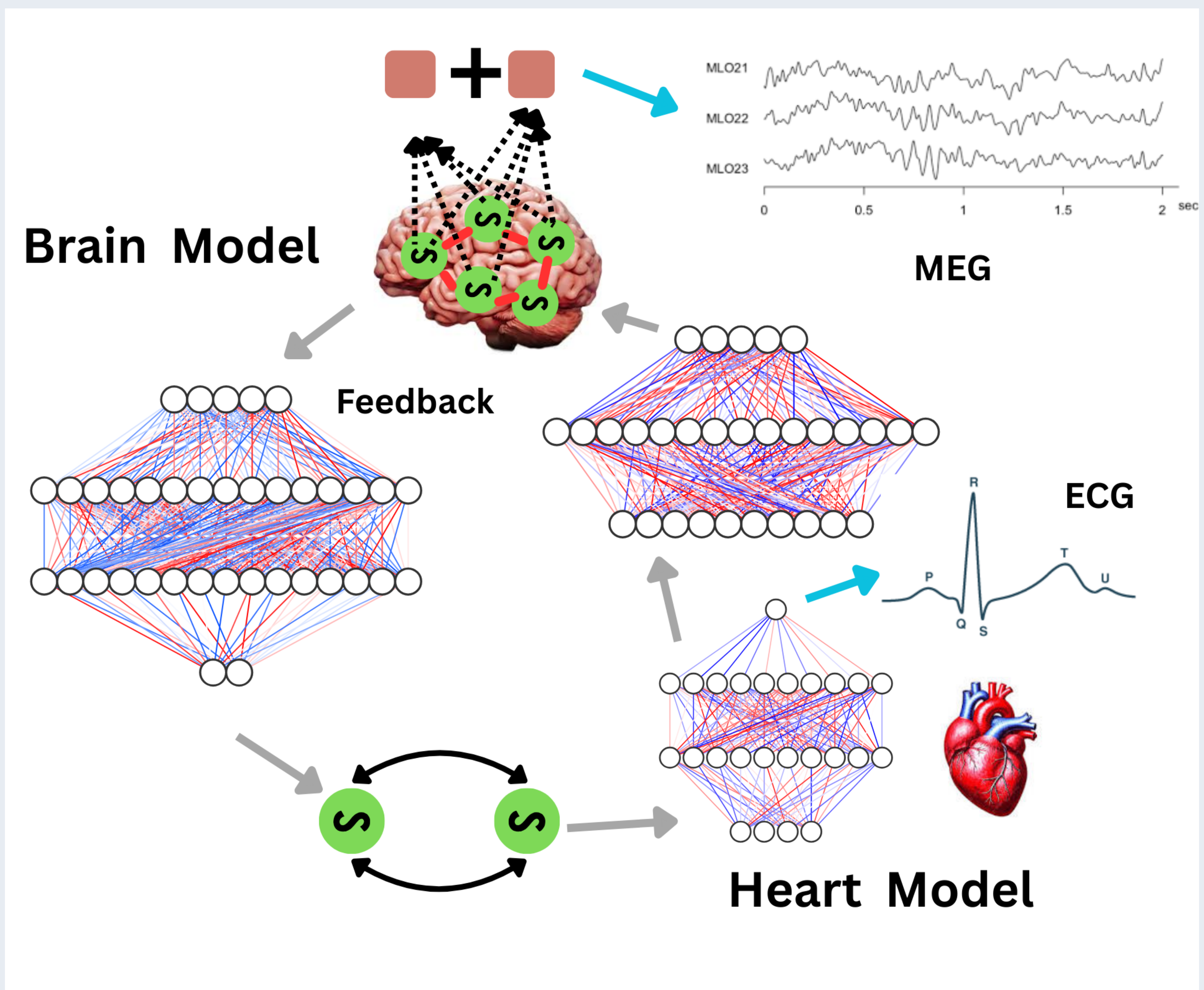
Dataset

- **CAM-CAN** MEG dataset comprising 122 MEG channels along with ECG and EOG recordings (sampling rate: 1000 Hz, downsampled to 100 Hz).
- Non-cardiac artifacts removed; ECG-related components preserved in MEG signals.
- Source reconstruction performed using **sLORETA**, projecting MEG signals onto individual anatomical MRI space.
- Cortical activity summarized across **68 regions of interest** using the Desikan–Killiany atlas.

Results



Model Architecture



Model Overview

We model brain–heart interactions using a **oscillatory deep-layer network with closed loop**, where latent cortical dynamics are represented by adaptive coupled oscillators that learn non-stationary rhythms through error-driven parameter evolution.

ECG Pretraining → Neural Dynamics Adaptation → Cross-Modal Mapping → Feedback Loop

Figure 2:Model Flowchart

Model Equations

State Dynamics:

$$\dot{r}_i = (\mu - r_i^2) r_i + \mathcal{I}_{\text{heart}} + \sum_j S_{ij} r_j^{\frac{\omega_i}{\omega_j}} cos(\Phi_{ij})$$

$$\dot{\phi}_i = \omega_i + \sum_j S_{ij} \frac{r_j^{\frac{\omega_i}{\omega_j}}}{r_i} \sin(\Phi_{ij})$$

Prediction:

$$\hat{D} = \sum_i \alpha_i r_i \cos(\phi_i), \qquad e = D - \hat{D}$$

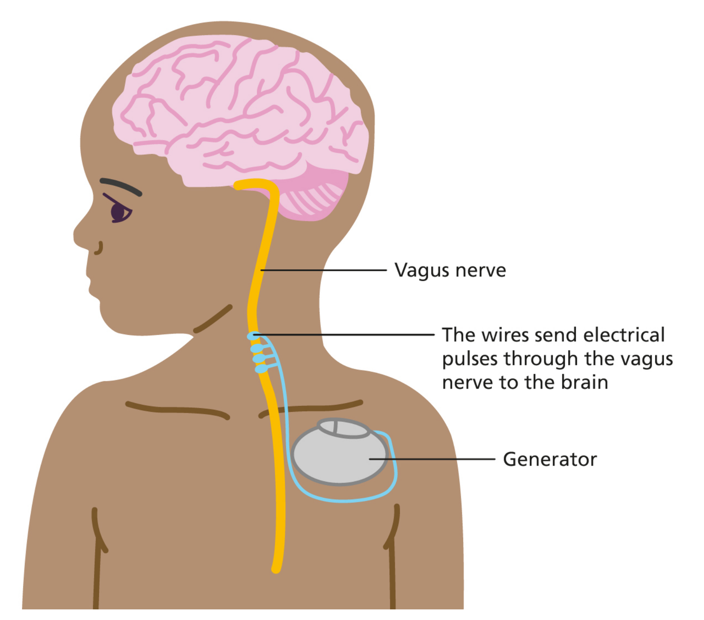
Adaptive Learning Rules:

$$\dot{\omega}_i = -\eta_\omega e \sin(\phi_i) \tag{1}$$

$$\dot{\alpha}_i = \eta_\alpha e r_i \cos(\phi_i) \tag{2}$$

Future Directions

- **VNS Modeling:** Simulate vagal stimulation via latent-space perturbations to study closed-loop neural–cardiac modulation.



- **HER Analysis:** Use the generative model to probe heartbeat-locked neural excitability and phase dynamics.
- **Coupling Hubs:** Identify cortical regions with strongest cardiac coupling across a 68-region atlas and verify the model output with anatomical data.

References

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[2] A. Bandyopadhyay, V. S. Chakravarthy, and D. Roy, "A mechanistic whole brain model to capture simultaneous eeg-fmri data," *bioRxiv*, 2025.

[3] K. Saluja, D. Roy, and A. Banerjee, "Age associated alterations in the cortical representation of cardiac signals," *bioRxiv*, 2024.