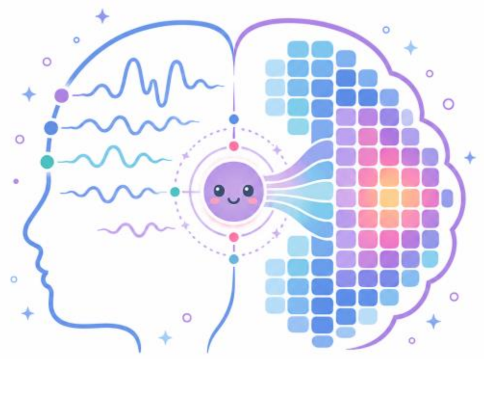


Mind the State: Towards Unified, Context-Aware EEG-to-fMRI Synthesis

Yamin Li[1], Shiyu Wang[1], Chang Li[1], Ange Lou[1], Haatef Pourmotabbed[1], Sarah Goodale[1,2], Dario J. Englot[1,2], Daniel Moyer[1], Roza G Bayrak[1], Catie Chang[1]

[1]Vanderbilt University, [2]Vanderbilt University Medical Center {yamin.li, catie.chang}@vanderbilt.edu

Project Page

Contact Author

Lab page: www.cchanglab.net/home

Take-Away

- We propose ***UniEFS***: a unified model for whole-brain fMRI synthesis from EEG.
- ***UniEFS*** learns fMRI-enhanced EEG representations that show potential transferability to broader downstream settings beyond paired EEG–fMRI data.

Introduction

EEG-to-fMRI translation enables cost-effective functional brain imaging.

The Challenge & Gap

Several frameworks for EEG-to-fMRI reconstruction have been proposed (e.g., [1, 5-7]), but are limited in one or more of the following ways:

- **Region-specific models** have limited scalability & efficiency
- Models **without full-brain coverage** may miss broader brain dynamics
- There has been **limited modeling of state and trait-level variability**: EEG-fMRI correlation is *dynamic*. Previous work overlooks inter-scan variability driven by demographic factors and time-varying physiological states

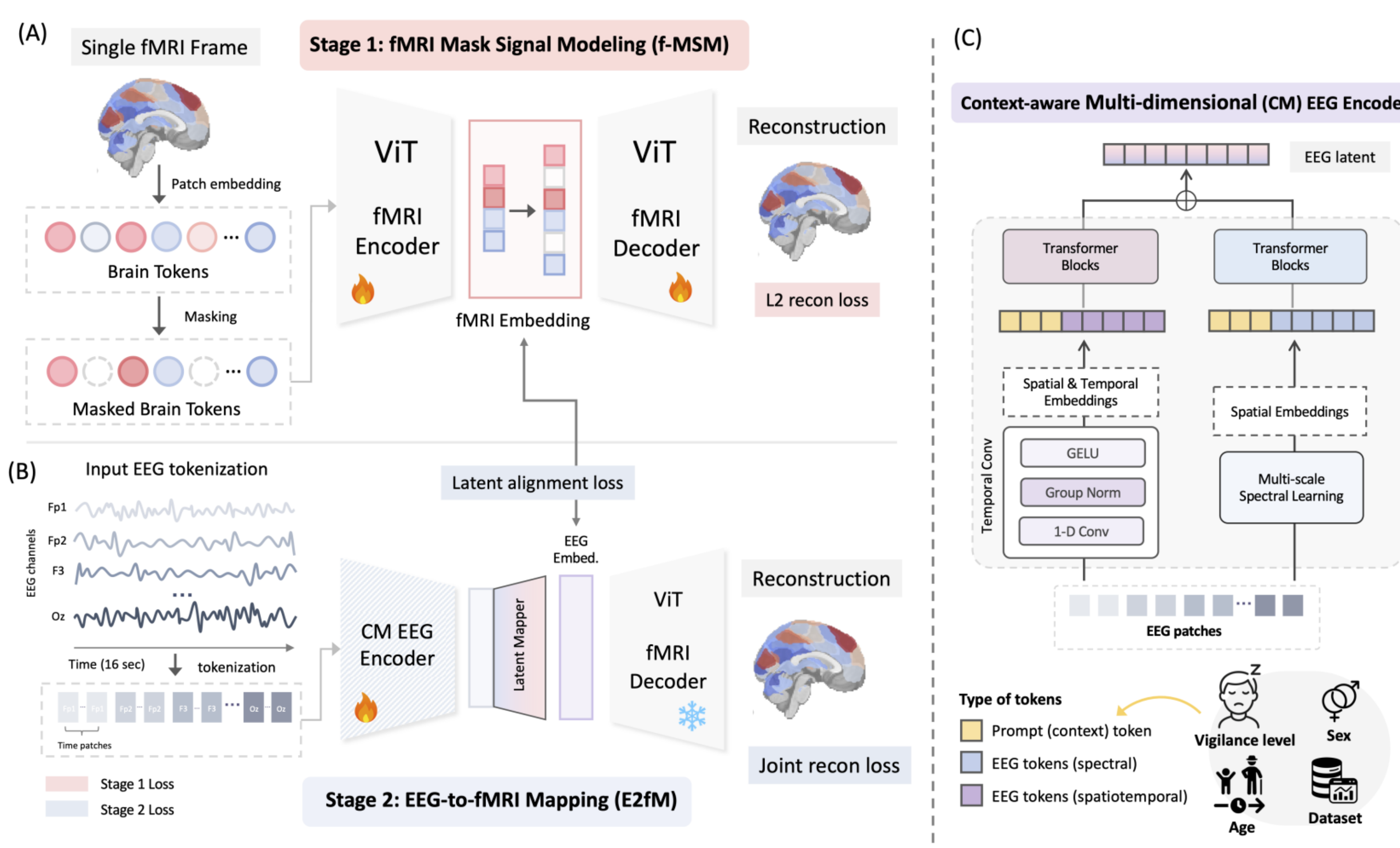
Other Challenges:

- Inferring **whole-brain** activity from **sparse** EEG measurements (23 channels) under ***limited*** paired data

Our Contributions

- **Unified model:** one model for full-brain coverage fMRI synthesis
- **Strong spatial priors:** learned through unpaired fMRI pretraining to support robust reconstruction.
- **Context-conditioned synthesis:** prompt tokens encode *dataset, age, sex, and vigilance* information to better model ***state-level*** variability.
- **Broad evaluation:** tested on resting-state, rest-to-task transfer, cross-dataset, and clinical EEG-only settings.

Method: UniEFS – Unified EEG-to-fMRI Synthesis



Pipelines

- **Frame-wise prediction - Input & Output:** Input: Preprocessed (MRI artifact reduction applied, resampled to 200Hz, normalized) EEG window (T=16s) before fMRI collection at time *t*: $X_{t-T:t-1}$. Output: fMRI values of all ROIs at time *t*: Y_t.
- **(A) Stage 1 – fMRI SSL pretraining via mask signal modeling:** Pretraining encoder-decoder on large-scale unpaired fMRI data (**HCP-YA**, 512 DiFuMo [4] ROIs).
- **(B) Stage 2 – context-aware EEG-to-fMRI mapping:** Encode EEG spatiotemporal and multi-scale spectral features with dataset-, subject-, and state-level context, align them to the frozen fMRI latent space, and decode fMRI using the pretrained decoder. Loss: Latent-alignment (MSE) + reconstruction (MSE + spatial-correlation) losses.

Simultaneous EEG-fMRI Datasets

Eyes-closed Resting-state (RS) Datasets:

Dataset 1 [1]

- **Overview:** 29 scans from 22 healthy volunteers
- **fMRI:** 3T, Philips scanner, TR=2.1s; **EEG:** 32-channel cap, 23 channels were used (those shared in common across the 3 datasets)

Dataset 2

- **Overview:** 10 training scans from 7 healthy volunteers, serving as additional training samples for main experiments
- **fMRI:** 3T Siemens Prisma scanner, TR=2.1s; **EEG:** 32-channel cap, 23 channels were used (those shared in common across the 3 datasets)

Auditory-task Dataset [1]: eyes closed, make a right-handed button press as soon as possible upon hearing a binaural tone

- **Overview:** 16 scans from 10 healthy volunteers
- **Scan duration:** 500 TR (17.5mins) for 6 scans, 693 TR (about 24 mins) for 10 scans
- **fMRI:** 3T Siemens Prisma scanner, TR = 2.1s; **EEG:** 32-channel cap, 23 channels were used (those shared in common across the 3 datasets)

Vigilance label: derived by VIGALL [2]

Evaluation Strategy

- Unseen-subject prediction: Predict full ~20-min, 512-ROI fMRI time series from EEG, with no subject overlap across splits.
- Cross-dataset / cross-condition transfer: Test robustness across sites, scanners, and resting/task conditions.
- Metrics: ROI-level temporal correlation for time-series reconstruction; element-wise MSE and correlation for functional connectivity (FC) reconstruction; predicted FC fingerprinting accuracy (see appendix)
- OOD EEG-only transfer: Probe learned fMRI-informed EEG representations on external EEG-only datasets with different populations and data distributions using downstream classification task.

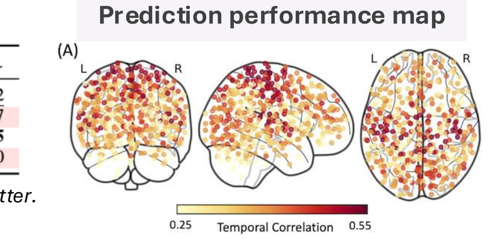
Key Results

1 Resting-state Prediction Performance

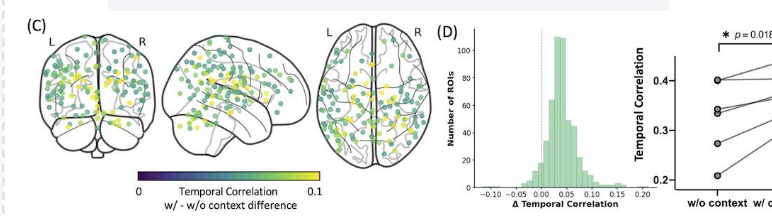
Model Name	MM	FB TCorr ↑	GM TCorr ↑	SC TCorr ↑	CB TCorr ↑	Conn Corr ↑	Conn MSE ↓
Ours	✓	**0.367 ± 0.052**	**0.394 ± 0.060**	**0.276 ± 0.082**	**0.247 ± 0.060**	0.527 ± 0.084	0.233 ± 0.072
NeuroBOLT (Li et al., 2024b)	✗	0.331 ± 0.044	0.357 ± 0.049	0.258 ± 0.092	0.216 ± 0.046	0.455 ± 0.079	0.349 ± 0.097
Li et al. (Li et al., 2024a)	✗	0.312 ± 0.038	0.329 ± 0.037	0.253 ± 0.090	0.236 ± 0.058	**0.535 ± 0.077**	**0.217 ± 0.065**
BEIRA (Kovalev et al., 2022)	✗	0.171 ± 0.148	0.196 ± 0.170	0.086 ± 0.085	0.063 ± 0.073	0.459 ± 0.080	0.368 ± 0.090

MM: Multiregion modeling. *Blue ($p < 0.05$), yellow ($p < 0.01$), red ($p < 0.001$) in paired t-test.* **FB:** *Full Brain.* **GM:** *Gray Matter.* **SC:** *SubCortical.* **CB:** *Cerebellum.* **Conn:** *FC matrix.* **MSE:** *element-wise MSE*

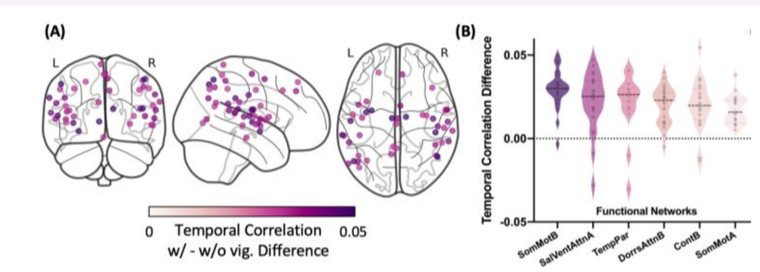
Prediction performance map



Performance gain from context embedding

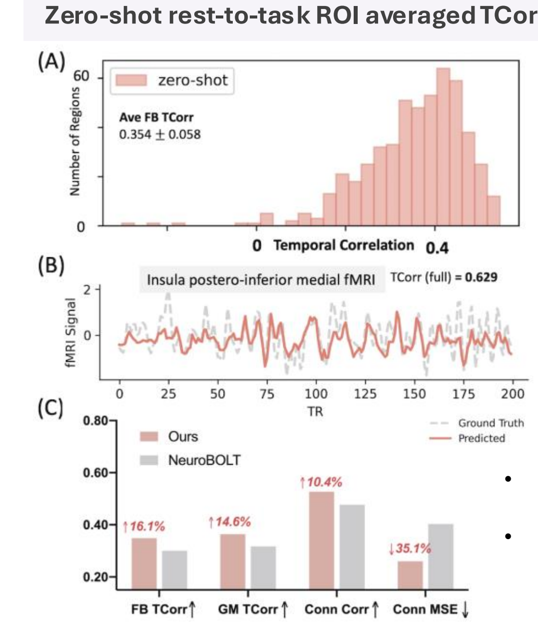


Vigilance tokens help improve prediction for regions related with vigilance

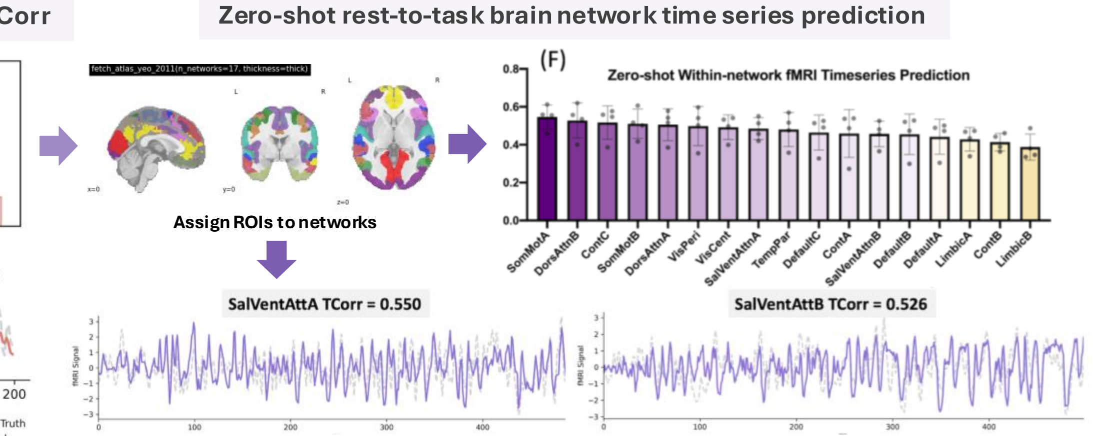


2 Resting-state to Task Transfer

Zero-shot rest-to-task ROI averaged TCorr

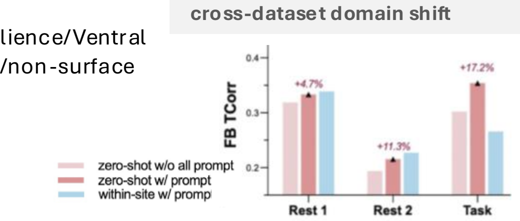


Zero-shot rest-to-task brain network time series prediction

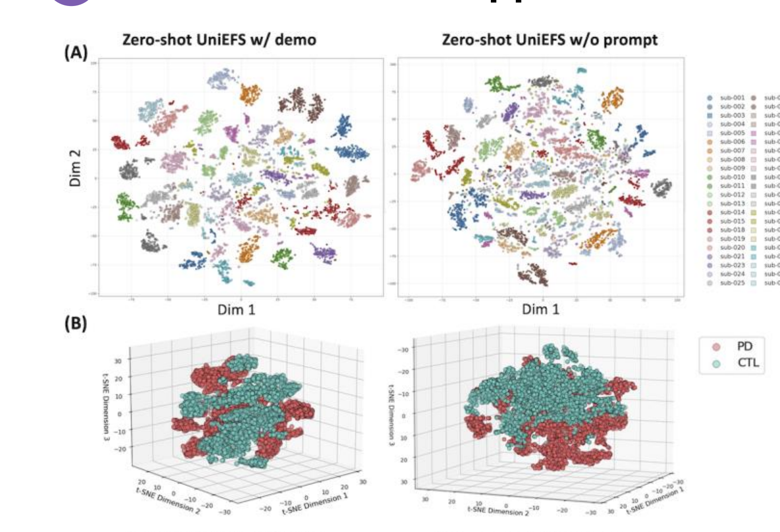


- Achieves consistently strong zero-shot reconstruction across functional networks.
- Recovers coherent temporal dynamics within the Salience/Ventral Attention Network, which includes challenging deep/non-surface regions such as anterior insula and dorsal ACC.

Context-aware modeling mitigates cross-dataset domain shift



3 Clinical zero-shot application with only EEG



Zero-shot generated latent on Parkinson EEG-only datasets [3] (22 healthy controls, 22 PD patients)

Transfer to Different task, Different population, Different age distribution

Linear Probing for HC/PD classification

Model	PD Acc ↑	PD F1 ↑	PD AUC ↑
UniEFS (w/ context)	**0.75**	**0.73**	**0.87**
UniEFS (w/o context)	0.68	0.67	0.79
UniEFS (w/o pretrain)	0.60	0.62	0.70
LaBraM (Jiang et al., 2024)	0.73	0.71	0.86
CBraMod (Wang et al., 2025a)	0.70	0.67	0.71

Acknowledgements

- The authors would like to acknowledge the **Advanced MRI Section of the NINDS, NIH**, where a subset of the data were collected. The authors are also grateful to **Caroline Martin** for assistance with data acquisition.
- This work was supported in part by NIH grants R01NS112252 and F31NS143413.

References

[1] NeuroBOLT, Li et al., NeurIPS, 2024. **[2]** VIGALL, Olbrich et al., 2015. **[3]** Cavanagh et al, OpenNeuro, 2021. **[4]** Difumo, Dadi et al., NeuroImage, 2020
[5] BEIRA, Kovalev et al., preprint, 2022. **[6]** CATD, Yao et al., IEEE TMI, 2024. **[7]** Li et al., SPIE Medical Imaging, 2024.