Supplementary Information

MEGaNorm: Normative Modeling of MEG Brain Oscillations Across the Human Lifespan

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Supplementary Methods

The SHASH likelihood

The SHASH distribution [1] incorporates four key parameters—mean (μ), variance (σ), skewness (ϵ), and kurtosis (δ), when defining the likelihood in the Bayesian modeling framework [2]. Unlike the Gaussian distribution ($X \sim N(\mu, \sigma)$), which depends solely on the location μ and scale σ parameters, the SHASH distribution models also the shape of the distribution by applying an inverse sinh-arcsinh transformation to samples drawn from a standard Gaussian distribution ($Z \sim N(0, 1)$):

$$\xi^{-1}_{\epsilon,\delta}(z) = \sinh\left(\frac{\sinh^{-1}(z) + \epsilon}{\delta}\right)$$

Here, z represents samples from a standard Gaussian distribution, and the transformation results in a SHASH distribution $S(\epsilon, \delta)$, where the parameters ϵ and δ control the skewness and kurtosis of the distribution, respectively. Specifically, ϵ adjusts the asymmetry of the distribution (skewness), while δ governs the tail behavior (kurtosis), allowing the SHASH distribution to model a wide range of non-Gaussian data shapes. The location (μ) and scale ($\sigma$of the distribution are also incorporated as follows:

$$\Omega = \xi_{\epsilon,\delta}^{-1}(Z)\sigma + \mu$$

where $\Omega \sim \mathcal{S}(\mu, \sigma, \epsilon, \delta)$. Together, the four parameters enable the SHASH distribution to accurately capture complex characteristics of data distribution, such as non-Gaussianity, and varying skewness or kurtosis.

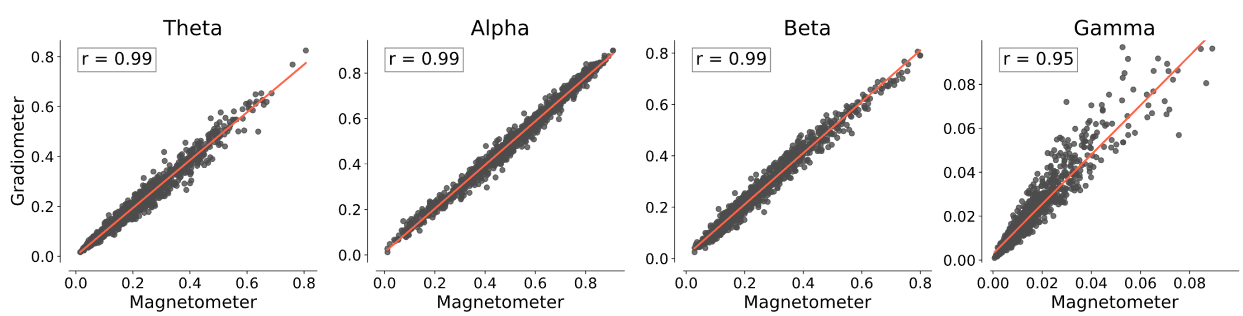
Excluded participants

Some participants were excluded from the analysis for the following reasons: missing demographic information, missing magnetoencephalography (MEG) recordings, and failure to fit models using the spectral parameterization algorithm. The table below summarizes the number of excluded participants per dataset:

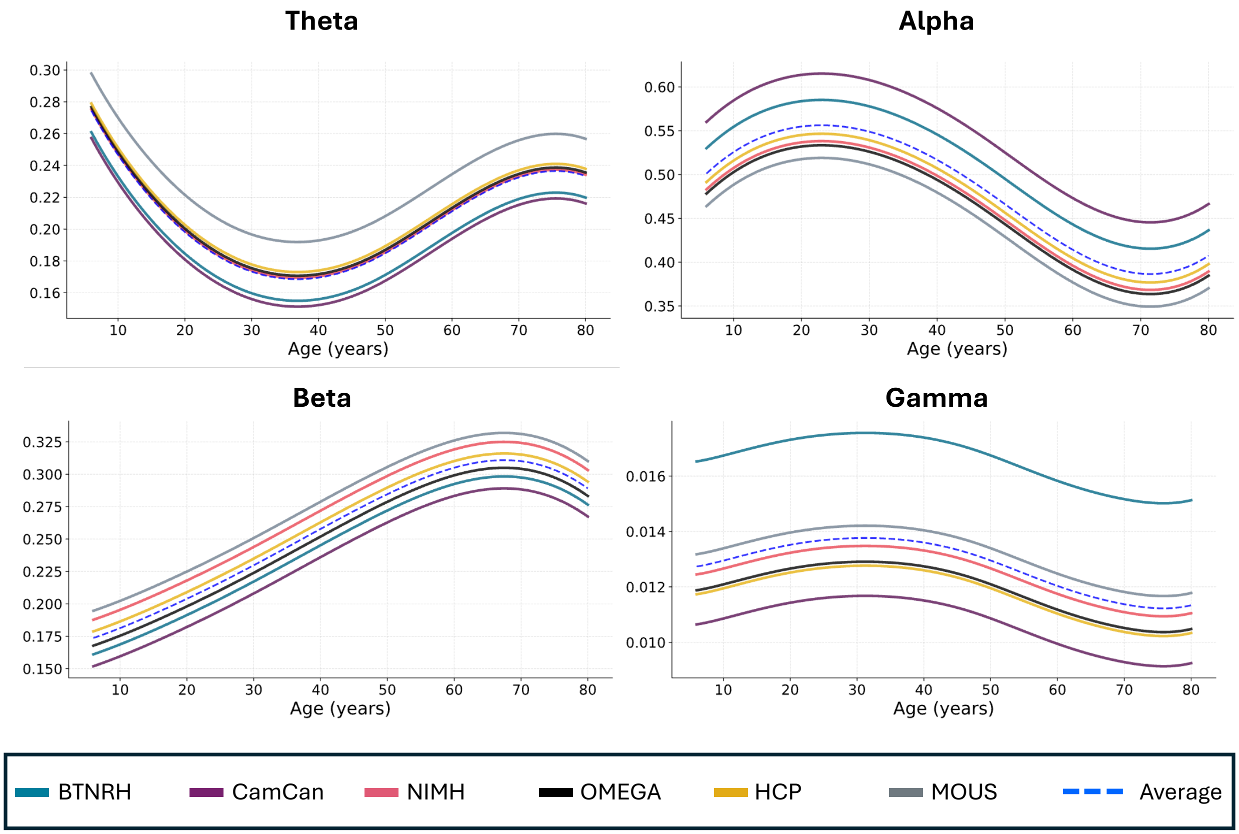
Supplementary Table 1: Number of excluded participants per dataset.

Scanner site	Number of excluded participants
BTH	0
CamCAN	20
NIMH	0
OMEGA	2
HCP	6
MOUS	5

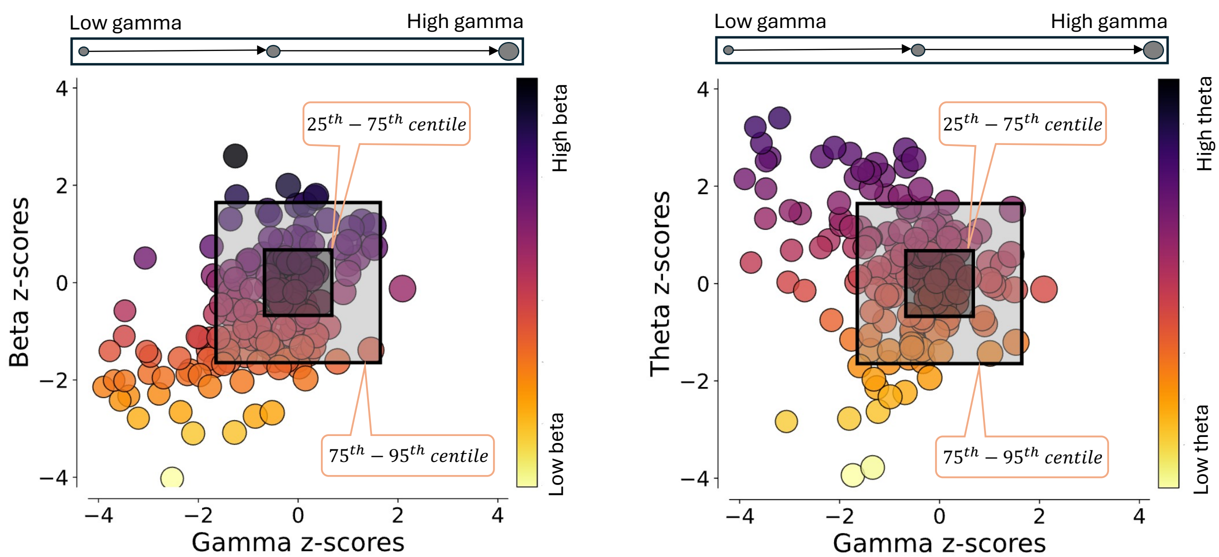
Supplementary Results



Supplementary Figure 1: The relative power of canonical frequency bands exhibited a high Pearson correlation across magnetometers and gradiometers. All Pearson correlation coefficients (r) were greater than 0.95.



Supplementary Figure 2: Lifespan 50^{th} centile trajectory of f-IDPs in males across six sites. The 50^{th} centile for each site is estimated by drawing samples from the posterior predictive distribution. Additionally, the average trajectory across sites is represented by a blue dashed line. The MOUS, OMEGA, and HCP datasets that were recorded in the eyes-closed condition exhibit a lower relative alpha power compared to the average.



Supplementary Figure 3: Scatter plot of the distribution of Parkinson's disease patients in gamma-beta and gamma-theta deviation space. The scatter plots highlight the heterogeneity in the patient population as spectra. Marker size represents the x-axis values, while the color map corresponds to the y-axis values.

References

[1] M Chris Jones and Arthur Pewsey. Sinh-arcsinh distributions. *Biometrika*, 96(4):761–780, 2009.

[2] Augustijn AA de Boer, Johanna MM Bayer, Seyed Mostafa Kia, Saige Rutherford, Mariam Zabihi, Charlotte Fraza, Pieter Barkema, Lars T Westlye, Ole A Andreassen, Max Hinne, et al. Non-gaussian normative modelling with hierarchical bayesian regression. *Imaging Neuroscience*, 2:1–36, 2024.