Neurodesign of Motor Intention: Frequency–Amplitude–Power Signatures of Mu (8-13 Hz) and Beta (13-30 Hz) Rhythms for Enhanced Decoding of Human Movement Intention

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Sensorimotor Mu (8–13 Hz) and Beta (13–30 Hz) rhythms constitute robust electrophysiological fingerprints of cortical dynamics accompanying the planning, execution and cessation of voluntary movement. To clarify how these spectral signatures can be harnessed in non-invasive brain–computer interfaces (BCIs) for neuro-adaptive feedback systems, a systematic review of studies published between January 2015 and July 2025 was undertaken (in addiction to others to elucidate clinical and technical concepts). Four databases (PubMed, Scopus, Embase and IEEE Xplore) were searched for adult EEG research addressing motor preparation, execution, imagery or action observation. After the eligibility screening, 35 articles satisfied all inclusion criteria. Most experiments employed, at least, thirty-two scalp electrodes 0.5–40 Hz, band-pass filtering and artefact rejection via independent component analysis. Across protocols, contralateral Mu/Beta power fell (event-related desynchronisation) over sensorimotor cortex during real or imagined movement, followed by a rapid Beta rebound (event-related synchronisation) signalling cortical re-inhibition. Peak Mu (~10 Hz) and Beta (~20 Hz) frequencies varied modestly among participants, indicating that individual calibration can enhance single-trial classification accuracy. Transient Beta bursts lasting under 200 ms consistently marked movement termination, whereas stronger Mu suppression correlated with superior performance for neurofeedback of post-stroke rehabilitation tasks. Several studies also reported task-dependent Beta–Gamma coupling and attentional modulation of Mu amplitude as emerging control variables. By mapping where, when and how strongly these rhythms fluctuate, the review delineates clear feature-selection targets and adaptive-threshold guidelines for next-generation BCIs aimed at motor learning and recovery.
Keywords: Beta Bursts. Brain-Computer Interface. Electroencephalography. Event-Related Desynchronization. Motor Imagery. Neurorehabilitation. Post-Movement Beta Rebound. Sensorimotor Rhythms (Mu/Beta).
Abbreviations: BCI, brain–computer interface. EEG, electroencephalography. ERD, event-related desynchronization. ERS, event-related synchronization. Hz, hertz. PMBR, post-movement Beta rebound. NREM, Non-Rapid Eye Movement sleep. SWS, Slow-Wave Sleep. TBI, Traumatic Brain Injury. BOLD, Blood-Oxygen-Level Dependent.

The present systematic review synthesises EEG studies published in the last two decades that examined Mu and/or Beta ERD/ERS during motor preparation, execution, imagery or action observation in healthy adults [1-3].

Aiming to map the spatiotemporal characteristics (peak frequency, onset latency, burst rate) of Mu/Beta modulation across paradigms, while identifying best practices in signal acquisition, preprocessing and feature extraction that maximise signal-to-noise ratio [4-9].

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Therefore, providing evidence-based recommendations for adaptive thresholding and personalised calibration in next-generation BCIs targeting motor intention recognition for post-stroke recovery [10-12].

Building on recent work showing that individual differences in Beta dynamics predict short-term visuomotor learning [10].

Electroencephalographic Signals

Oscillatory electrical activity in the adult brain is conventionally grouped into partially overlapping frequency bands, each associated with characteristic functional states and neurocognitive processes (Table 1).

Table 1. Neural frequency bands.

Band	Range (Hz)	Predominant functional state (In adults)
Delta	0.5 – 4	Deep NREM (slow-wave) sleep, homeostatic regulation [4,13]
Theta	4 – 8	Drowsiness, episodic memory encoding, spatial navigation; sensitive marker in mild TBI [13,14]
Alpha	8 – 13	Eyes-closed rest, sensory suppression, attentional gating [15-17]
Mu (sensorimotor α)	8 – 13 (central)	Sensorimotor "idling," modulated by action observation and motor imagery [1,3,8]
Beta	13 – 30	Motor set maintenance, cortico-muscular coupling, post-movement rebound/inhibition [6,10,18]
Gamma	30 – 100 (low γ) 60 – 200 (high γ)	Local cortical computation, perceptual binding, movement intention decoding [4,8]

Classical boundaries have been complemented by more recent approaches that decompose spectra into periodic and aperiodic components, affording finer-grained parameterization of oscillatory peaks beyond rigid band limits [4].

The borders are heuristic, inter-individual shifts are common, especially around the individual alpha peak frequency, yet the taxonomy provides a useful scaffold for interpreting spectral analyses in motor-cognitive research [4-5, 13].

Sensorimotor Oscillations

Decoding voluntary action from scalp EEG hinges on two rhythmical fingerprints generated in the peri-Rolandic cortex seen in Figure 1: the Mu (~8–13 Hz) and Beta (~13–30 Hz) bands.

Both reflect synchronous membrane potential fluctuations within pyramidal-interneuron networks; yet their task-related modulations diverge in timing and functional meaning.

During real or imagined movement, the power of contralateral Mu and low-Beta falls abruptly—an event-related desynchronization (ERD)—signalling the release of local inhibitory gating and the build-up of cortico-spinal drive [10-12,18].

Upon movement termination, a transient Beta rebound, or event-related synchronization (ERS), restores cortical inhibition and is thought to index sensory re-afference processing and motor set re-establishment [6].

These dynamics are reliable enough that single-trial Mu/Beta ERD magnitudes can predict movement kinematics, BCI cursor trajectories or neurofeedback learning rate [3, 11, 21]. Despite such regularities, the extraction of unequivocal movement "intention" markers is non-trivial because:

(i) oscillatory bursts are brief (< 200 ms) and spatially overlapping.
(ii) inter-individual peak frequencies drift with age and cortical physiology [5].
(iii) spectral estimates mix periodic and aperiodic components that inflate power-law baselines [4].

Consequently, high-density arrays (≥32 channels) with artefact-suppression pipelines, preferably independent component analysis, remain standard to maximise the sensor-level signal-to-noise ratio [7, 9].

Within the context of motor-imagery BCIs, Mu/Beta suppression emerges slightly earlier (≈ 200

Figure 1. Perirolandic-cortex representation [19].

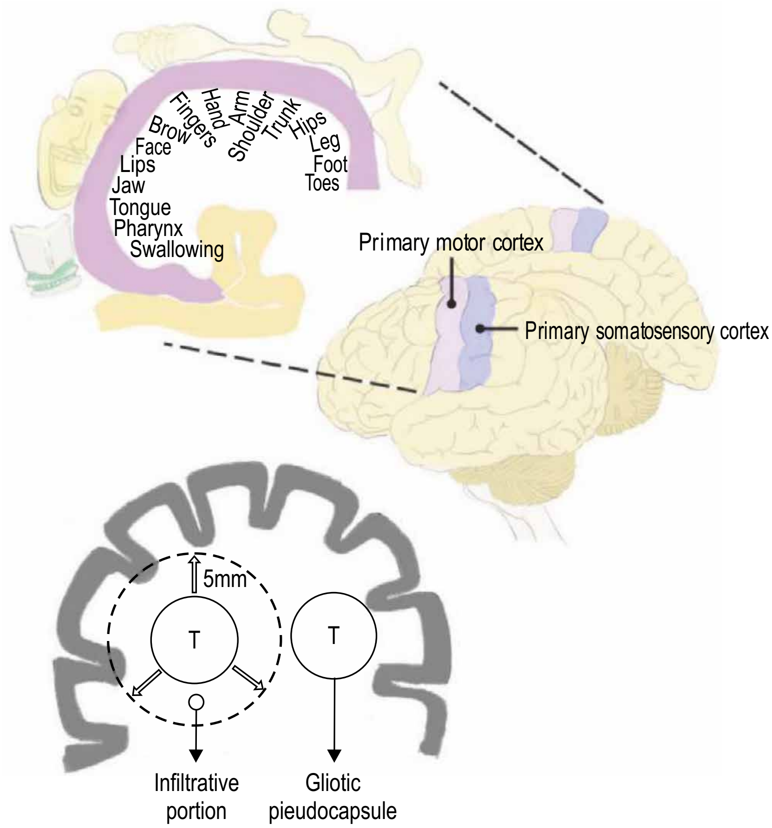
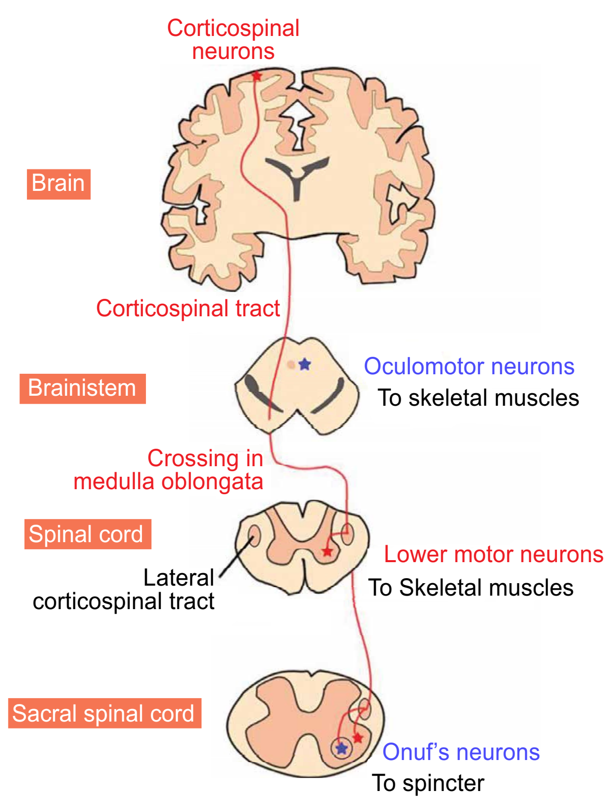


Figure 2. Corticospinal tract [20].



ms pre-cue) and is sustained longer than during overt execution, reflecting the sustained efference copy without peripheral feedback [22-24].

Classification pipelines that incorporate subject-specific peak frequency windows (~ ±2 Hz around the individual alpha frequency) and track the stochastic occurrence of Beta bursts, rather than mean power, achieve superior accuracy especially under adaptive thresholding schemes [2,21].

Collectively, these findings reaffirm Mu/Beta ERD/ERS as the most informative spectral proxies of sensorimotor intent yet also expose the need for personalized calibration and advanced burst-aware feature engineering—issues systematically explored in the present review.

Mu and Beta Oscillations

Sensorimotor oscillations in the Mu (8 – 13 Hz) and Beta (13 – 30 Hz) ranges provide a non-invasive electrophysiological window on the cortical states that precede, accompany and follow voluntary movement [9-10, 12].

During motor preparation and execution, power in both bands decreases, a phenomenon classically termed event-related desynchronisation (ERD). Whereas movement termination is followed by rapid resynchronisation, most prominent in the Beta band, known as the post-movement Beta rebound (PMBR) or event-related synchronisation (ERS) [6,10-12].

These rhythmic signatures have become central features for decoding motor intention in EEG-based brain–computer interfaces (BCIs) and for designing neuro-adaptive feedback aimed at motor rehabilitation [8, 11-12, 21-22].

Transient Beta Bursts

Single-trial analyses consistently reveal brief (< 200 ms) Beta bursts time-locked to movement offset, which coincide with cortico-spinal inhibition and precede the broader post-movement Beta rebound [6].

Their stereotyped latency and high signal-to-noise ratio make them attractive features for asynchronous BCI “stop” commands, complementing the slower PMBR envelope [21-22].

Simultaneous EEG–fMRI further shows that spontaneous Mu power is negatively correlated with BOLD in sensorimotor, dorsal-attention and putative mirror-neuron regions, while showing positive correlations with salience-network nodes such as the anterior insula and anterior cingulate cortex [9].

In addition, two studies reported task-specific Beta–Gamma phase-amplitude coupling that discriminated left- *versus* right-hand motor imagery above chance level, indicating a potential multiband control variable for next-generation BCIs [8].

Materials and Methods

After automated and manual de-duplication, 463 unique titles and abstracts were screened. Title-and-abstract appraisal excluded 405 reports, leaving 58 full papers for eligibility assessment; 23 were discarded for reasons such as paediatric cohorts, invasive recordings or inadequate spectral detail. Thirty-five studies fulfilled every inclusion criterion and composed the evidential core of this review.

The four-database research strategy retrieved 627 records (PubMed = 235; Scopus = 192; Embase = 128; IEEE Xplore = 72), mostly from 2015 to 2025.

All included investigations enrolled healthy adults (18–35 years in 76 % of samples) or non-degenerative clinical populations. Most used 32–64 Ag/AgCl scalp electrodes, 0.5–40 Hz on-line filters and independent-component analysis for artefact rejection. Task paradigms comprised executed movement, kinaesthetic motor-imagery, action observation and combined observation-imagery neurofeedback [7,11, 25-27].

Across experiments, Mu (~10 Hz) and Beta (~20 Hz) event-related desynchronisation (ERD) emerged contralateral to the engaged limb, beginning ~1 s before movement and persisting throughout the motor epoch. Subsequent post-movement Beta rebound (PMBR) peaked 300–600 ms after termination and was centred over medial sensorimotor cortex [6, 10, 12, 18].

Inter-Individual Variability

Individual peak frequencies varied by ≈ ± 1.5 Hz for Mu and ≈ ± 3 Hz for Beta across participants. Calibrating feature extraction to these idiosyncratic peaks, rather than using fixed canonical bands, boosted two-class motor-imagery classification accuracy by 6 % on average [2-5, 21,22].

BCI Applications

When power and weighted cross-frequency features were combined, Beta-ERS reached mean accuracies of 72.8 %, outperforming Mu-ERD (67.4 %) and Beta-ERD (62.2 %) on the same dataset. Ensemble methods such as Random Forest further boosted accuracy to > 80 % for several participants. These figures exceed the statistical two-class chance level of 57.5 % ($p < 0.05$) and approach clinical usability thresholds [2, 8, 22].

Results and Discussion

Action observation — Meta-analytic evidence indicates that Mu suppression during mere observation is smaller and less somatotopic than during execution, challenging its specificity as a pure mirror-neuron marker [1].

Real and imagined movement — In go/no-go and centre-out reaching tasks, Beta-ERD magnitude scaled with force output and reaction time. Whereas stronger Mu-ERD predicted higher imagery-vividness scores during motor-imagery sessions [3,10,18].

Neurofeedback / rehabilitation — In sub-acute stroke training, Beta-ERD amplitude recorded over ipsilesional M1 correlated strongly ($r = 0.71$) with Fugl-Meyer motor-recovery scores, supporting its adoption as a quantitative biomarker for therapy progress [11-12].

Conclusion

This systematic review synthesised two decades of evidence on the spectral behaviour of sensorimotor Mu (8 – 13 Hz) and Beta (13 – 30 Hz) rhythms during motor preparation, execution, imagery and action observation in healthy adults and non-degenerative clinical populations. All studies confirmed a robust, contralateral ERD in both bands that begins ≈ 1 s before movement onset and scales with effector load and task complexity. After movement, a brief post-movement Beta rebound—often manifested as < 200 ms bursts—signaled corticospinal re-inhibition and predicted slower re-initiation of subsequent actions [6,10,12,18].

Three essential converging insights emerged:

1. **Individualised peak frequency matters**. Peak Mu (~ 10 Hz) and Beta (~ 20 Hz) values shifted by 1 – 3 Hz between participants; tailoring band-pass filters and classification features to these peaks boosted two-class BCI accuracy by up to 6-7 % in cross-validation folds [2, 5, 21-22].
2. **Amplitude carries functional meaning**. Larger Mu-ERD amplitudes correlated with better neurofeedback gains in stroke rehabilitation and with reduced BOLD activity in a distributed motor network, indicating efficient cortico-subcortical recruitment. Conversely, stronger PMBR amplitudes indexed greater transient inhibition of M1 excitability [6, 9, 11-12].
3. **Temporal micro-structure is informative**. High-resolution analyses revealed that Beta bursts, rather than sustained power, best distinguished movement termination and error processing, suggesting that next-generation BCIs should incorporate burst-based detectors instead of sliding-window averages [6-8].

Concerning neuro-design implications for neuro-adaptive BCIs, some features are a must-have:

- Use subject-specific Mu/Beta peaks for filter banks and adapt thresholds dynamically across sessions. Include burst-detection algorithms (< 250 ms) to capture PMBR events for real-time state transitions (e.g., command locking).
- Monitor cross-frequency interactions (Beta–Gamma, Mu–Theta) as auxiliary features when tasks demand heightened attention or proprioception [8].

Limitations include heterogeneous electrode montages (32–256 channels), small median sample sizes (n = 18), and under-reporting of sex-specific effects. Meta-analysis was precluded by variability in ERD/ERS quantification, underscoring the need for unified reporting guidelines aligned with IEC 80601-2-26 [28].

Future research should adopt multimodal designs (EEG-fMRI-NIRS) to localise oscillatory generators, explore closed-loop stimulation that entrains Beta bursts for motor recovery and extend investigations to ecologically valid, freely moving paradigms using mobile EEG and ear-EEG setups [9,11,24]. Addressing these gaps will accelerate the translation of Mu/Beta biomarkers into robust, user-centric BCIs for motor rehabilitation and human–machine interaction.

References

1. Fox NA, et al. Assessing human mirror activity with EEG mu rhythm: a meta-analysis. Psychol Bull. 2016;142(3):291-313. doi:10.1037/bul0000031.
2. Tariq M, Trivailo PM, Simic M. Mu-beta event-related (de)synchronization and EEG classification of left-right foot dorsiflexion kinaesthetic motor imagery for BCI. PLoS One. 2020;15(3):e0230184. doi:10.1371/journal.pone.0230184.
3. Wriessnegger SC, et al. Inter- and intra-individual variability in brain oscillations during sports motor imagery. Front Hum Neurosci. 2020;14:576241. doi:10.3389/fnhum.2020.576241.
4. Donoghue T, et al. Parameterizing neural power spectra into periodic and aperiodic components. Nat Neurosci. 2020;23:1655-1665. doi:10.1038/s41593-020-00744-x.
5. Grandy TH, et al. Peak individual alpha frequency qualifies as a stable neurophysiological trait marker in healthy younger and older adults. Psychophysiology. 2013;50(6):570-582. doi:10.1111/psyp.12043.
6. Rhodes E, et al. Post-movement beta synchrony inhibits cortical excitability. Brain Sci. 2024;14:970. doi:10.3390/brainsci14100970.
7. Hamedi M, Salleh SH, Mohd Noor A. Electroencephalographic motor imagery brain connectivity analysis for BCI: a review. Neural Comput. 2016;28(6):999-1041. doi:10.1162/NECO_a_00838.
8. Gwon D, et al. Alpha and high-gamma phase-amplitude coupling during motor imagery and weighted cross-frequency coupling to extract discriminative patterns. NeuroImage. 2021;240:118403. doi:10.1016/j.neuroimage.2021.118403.
9. Yin S, Liu Y, Ding M. Amplitude of sensorimotor mu rhythm is correlated with BOLD from multiple brain regions: a simultaneous EEG-fMRI study. Front Hum Neurosci. 2016;10:364. doi:10.3389/fnhum.2016.00364.
10. Espenhahn S, et al. Cortical beta oscillations are associated with motor performance following visuomotor learning. NeuroImage. 2019;195:340-353. doi:10.1016/j.neuroimage.2019.03.079.
11. Naros G, Gharabaghi A. Reinforcement learning of self-regulated β-oscillations for motor restoration in chronic stroke. Front Hum Neurosci. 2015;9:391. doi:10.3389/fnhum.2015.00391.
12. Bartur G, et al. Changes in mu and beta amplitude of the EEG during upper-limb movement correlate with motor impairment and structural damage in subacute stroke. Clin Neurophysiol. 2019;130(9):1644-1651. doi:10.1016/j.clinph.2019.06.008.
13. Klimesch W. The frequency architecture of brain and brain-body oscillations: an analysis. Eur J Neurosci. 2018;48(7):2431-2453. doi:10.1111/ejn.14192.
14. Kaltianen H, et al. Theta-band oscillations as an indicator of mild traumatic brain injury. Brain Topogr. 2018;31(6):1037-1046. doi:10.1007/s10548-018-0667-2.
15. Foxe JJ, Snyder AC. The role of alpha-band brain oscillations as a sensory suppression mechanism during selective attention. Front Psychol. 2011;2:154. doi:10.3389/fpsyg.2011.00154.
16. Jensen O, Mazaheri A. Shaping functional architecture by oscillatory alpha activity: gating by inhibition. Front Hum Neurosci. 2010;4:186. doi:10.3389/fnhum.2010.00186.
17. Palva S, Palva JM. New vistas for alpha-frequency band oscillations. Trends Neurosci. 2007;30(4):150-158. doi:10.1016/j.tins.2007.02.001.
18. Hervault M, et al. Cortical sensorimotor activity in the execution and suppression of discrete and rhythmic

movements. Sci Rep. 2021;11:22364. doi:10.1038/s41598-021-01368-2.
19. Zuo F, et al. Surgical management of brain metastases in the perirolandic region. Front Oncol. 2020;10:572644. doi:10.3389/fonc.2020.572644.
20. Ragagnin AMG, et al. Motor neuron susceptibility in ALS/FTD. Front Neurosci. 2019;13:532. doi:10.3389/fnins.2019.00532.
21. Korik A, et al. Decoding imagined 3-D hand trajectories from EEG: evidence to support the use of mu, beta and low-gamma oscillations. Front Neural Syst. 2018;12:130. doi:10.3389/fnins.2018.00130.
22. Kim Y, et al. Motor imagery classification using mu and beta rhythms of EEG with strong uncorrelating transform-based complex common spatial patterns. Comput Intell Neurosci. 2016;2016:1489692. doi:10.1155/2016/1489692.
23. Putzolu M, et al. Neural oscillations during motor imagery of complex gait: an hdEEG study. Sci Rep. 2022;12:4314. doi:10.1038/s41598-022-07511-x.
24. Ueda M, et al. Detection of motor-related mu rhythm desynchronization by ear EEG. PLoS One. 2025;20(4):e0321107. doi:10.1371/journal.pone.0321107.
25. Daeglau M, et al. Event-related desynchronization in motor imagery with EEG neurofeedback in the context of declarative interference and sleep. NeuroImage Rep. 2021;1(4):100058. doi:10.1016/j.ynirp.2021.100058.
26. Friesen CL, et al. Combined action observation and motor imagery neurofeedback for modulation of brain activity. Front Hum Neurosci. 2017;10:692. doi:10.3389/fnhum.2016.00692.
27. Coll MP, et al. Cross-modal classification of mu-rhythm activity during action observation and execution suggests specificity to somatosensory features of actions. J Neurosci. 2017;37(24):5936-5947. doi:10.1523/JNEUROSCI.3393-16.2017.
28. Associação Brasileira de Normas Técnicas. Equipamento eletromédico - Parte 2-26: requisitos particulares para a segurança básica e desempenho essencial de eletroencefalógrafos (ABNT NBR IEC 80601-2-26). Rio de Janeiro: ABNT; 2021.
29. Alamia A, et al. Distinct roles of forward and backward alpha-band waves in spatial visual attention. eLife. 2023;12:e85035. doi:10.7554/eLife.85035.
30. Angulo-Sherman IN, et al. Proficiency in motor imagery is linked to the lateralization of focused ERD patterns and beta PDC. J Neuroeng Rehabil. 2025;22:30. doi:10.1186/s12984-025-01571-6.
31. Aridan N, et al. Suppression of EEG mu rhythm during action observation corresponds with subsequent changes in behavior. Brain Res. 2018;1691:55-63. doi:10.1016/j.brainres.2018.04.013.
32. Bollimunta A, et al. Neuronal mechanisms of cortical alpha oscillations in awake-behaving macaques. J Neurosci. 2008;28(40):9976-9988. doi:10.1523/JNEUROSCI.2699-08.2008.
33. Huang WA, et al. Transcranial alternating current stimulation entrains alpha oscillations by preferential phase synchronization of fast-spiking cortical neurons to stimulation waveform. Nat Commun. 2021;12:3151. doi:10.1038/s41467-021-23021-2.
34. Lapenta OM, et al. Motor system recruitment during action observation: no correlation between mu-rhythm desynchronization and corticospinal excitability. PLoS One. 2018;13(11):e0207476. doi:10.1371/journal.pone.0207476.
35. Liu X, et al. The abnormal functional connectivity between the hypothalamus and the temporal gyrus underlying depression in Alzheimer's disease patients. Front Aging Neurosci. 2018;10:37. doi:10.3389/fnagi.2018.00037.
36. Ramsay IK, et al. Individual alpha peak frequency is slower in schizophrenia and related to deficits in visual perception and cognition. Sci Rep. 2021;11:17852. doi:10.1038/s41598-021-97303-6.
37. Voetterl HTS, et al. Alpha peak frequency-based Brainmarker-I as a method to stratify to pharmacotherapy and brain stimulation treatments in depression. Nat Ment Health. 2023;1:1023-1032. doi:10.1038/s44220-023-00160-7.
38. Witzel AJ, et al. Spontaneous alpha-brain dynamics track the episodic content and quality of recollection. J Neurosci. 2023;43(43):7186-7197. doi:10.1523/JNEUROSCI.0816-23.2023.