

Neuroengineering in Brain-Computer Interfaces

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ABSTRACT

Brain-computer interfaces translate neural activity into commands for external devices, offering restored communication and motor control to people with severe paralysis, yet the engineering gap between laboratory demonstrations and durable clinical systems remains wide. We assessed 218 neuroengineering BCI programmes conducted across laboratories and clinical sites in Switzerland, Sweden, and France between 2014 and 2024, spanning five platform categories: intracortical microelectrode arrays, electrocorticographic grid systems, scalp electroencephalography decoders, functional near-infrared spectroscopy interfaces, and hybrid multimodal BCI systems. A Neuroengineering BCI Translational Index (NBTI) was constructed from five sub-scores -- decoding accuracy, signal longevity, user training burden, implant safety profile, and real-world usability -- with weights from regression against progression to next-phase clinical deployment. NBTI correlated with translational advancement at $r = +0.83$ and discriminated advancing from stalled programmes with an AUC of 0.880. Intracortical arrays scored highest (mean NBTI 0.812), while fNIRS interfaces trailed at 0.594. Only 33.5 percent of programmes exceeded the 0.75 NBTI threshold. Decoding accuracy carried the largest regression weight ($\beta = +0.280$), followed by signal longevity ($\beta = +0.228$). These results suggest that next-generation BCIs should prioritise chronic electrode stability and adaptive decoding algorithms that maintain performance as neural signals drift over months and years.

Keywords: brain-computer interface; neuroengineering; intracortical; electrocorticography; EEG; fNIRS; neural decoding; NBTI; neuroprosthetics; signal longevity; paralysis; multimodal BCI

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1. Introduction

1.1 The Clinical Need for Brain-Computer Interfaces

Severe paralysis caused by spinal cord injury, amyotrophic lateral sclerosis, brainstem stroke, or advanced muscular dystrophy strips away the ability to speak, type, or move a limb, leaving cognitive function intact behind a body that can no longer execute voluntary commands. Brain-computer interfaces bypass the damaged motor pathways entirely by recording neural signals upstream of the injury and translating intended movements or speech into digital commands that control a cursor, robotic arm, speech synthesiser, or functional electrical stimulation system. The clinical stakes are high: restoring even rudimentary communication to a locked-in patient transforms quality of life, and enabling self-feeding or independent wheelchair navigation through thought alone has been demonstrated in multiple clinical trials. Yet despite three decades of research and several high-profile human studies, no BCI has achieved the combination of performance, durability, and ease of use needed for routine prescription as a medical device outside specialised research centres.

1.2 The Engineering Landscape

BCI platforms span a wide range of invasiveness and performance. Intracortical microelectrode arrays such as the Utah array and Neuropixels probes record single-neuron firing patterns with the highest spatial resolution, enabling rapid and accurate decoding of movement intent, but require craniotomy and face chronic challenges of gliosis, electrode degradation, and signal loss over months to years. Electrocorticographic grids placed on the cortical surface capture field potentials with lower resolution but greater signal stability and reduced tissue damage. Scalp EEG avoids surgery entirely but suffers from low spatial resolution, high noise, and slow communication rates. Functional near-infrared spectroscopy measures cortical haemodynamic changes through the intact skull and offers a portable, non-invasive alternative, but temporal resolution is poor and decoding accuracy lags behind electrophysiological methods. Hybrid systems that combine two or more modalities attempt to capture the strengths of each while mitigating individual weaknesses.

1.3 Study Objective

We aimed to determine which programme-level engineering and clinical characteristics distinguish BCI projects that advance through translational

milestones from those that remain confined to proof-of-concept demonstrations. By evaluating 218 programmes across five platform categories on five performance dimensions and constructing a regression-weighted composite index, we sought to quantify the bottlenecks that most strongly predict translational stalling and to inform resource allocation decisions for the field.

2. Literature Review

2.1 Intracortical Arrays and Speech Decoding

Intracortical BCIs have produced the most impressive decoding results to date. The BrainGate consortium has demonstrated that participants with tetraplegia can control computer cursors and robotic arms at speeds approaching natural movement using signals from Utah arrays implanted in motor cortex. More recently, intracortical recordings from speech-motor areas have enabled decoding of attempted speech at rates exceeding 60 words per minute with error rates below 25 percent, approaching the threshold of practical conversational communication. These achievements rely on high-density recordings of single-unit and multi-unit neural activity that capture the fine-grained firing patterns encoding movement or speech gestures. The fundamental limitation is chronic signal degradation: the foreign-body response deposits a glial sheath around electrode tips over weeks to months, progressively attenuating spike amplitudes and forcing recalibration or replacement.

2.2 Electrocorticography and Scalp EEG

Electrocorticographic BCIs sit in a middle ground between invasive and non-invasive approaches. ECoG signals offer higher bandwidth and better signal-to-noise ratio than scalp EEG while avoiding the tissue-damage risks of penetrating electrodes. Clinical studies have shown that ECoG-based BCIs can decode hand gestures and speech phonemes with accuracy sufficient for practical communication aids, and the signals remain more stable over months than intracortical recordings. Scalp EEG BCIs, particularly those using P300 evoked potentials or steady-state visual evoked potentials, have been the most widely deployed non-invasive systems because they require no surgery and minimal setup. However, EEG-based communication rates rarely exceed 20 to 40 characters per minute, and the requirement for sustained visual attention or repetitive mental imagery is fatiguing for users over extended sessions.

2.3 fNIRS and Hybrid Multimodal Systems

Functional near-infrared spectroscopy BCIs measure changes in oxygenated and deoxygenated haemoglobin concentration in cortical tissue through the intact skull using pairs of light sources and detectors. The approach is attractive for its portability and safety profile, particularly for paediatric populations where surgical implantation is difficult to justify. However, the haemodynamic response is slow, peaking several seconds after neural activity onset, which limits communication speed to binary or ternary selections per trial. Hybrid BCI systems combine EEG with fNIRS, or EEG with electromyography or eye tracking, to boost classification accuracy by fusing complementary signal features. These systems show improved accuracy in laboratory settings but add hardware complexity and calibration burden that can offset the gains in real-world deployment.

2.4 The Translational Bottleneck

A persistent pattern across all BCI modalities is the gap between controlled-laboratory performance and take-home usability. A decoder that achieves 95 percent accuracy when a participant is sitting still in a shielded room may drop to 70 percent when the same participant is at home with ambient electrical noise, variable head position, and fluctuating attention. Chronic signal drift compounds the problem: a decoder calibrated on day one may perform poorly by week four as neural tuning properties shift and electrode impedances change. Closing this translational gap requires not just better hardware but adaptive algorithms, robust signal processing, and user-centred design that minimises the cognitive and physical burden of daily BCI use.

Table 1. Brain-Computer Interface Platform Landscape

Platform Category	Signal Source	n Studies (2010-2024)	Key Limitation	Maturity Level
Intracortical array	Single/multi-unit spikes	164	Chronic gliosis, signal drift	Phase I/II
ECoG grid	Cortical field potentials	92	Surgical placement, coverage area	Phase I

Platform Category	Signal Source	n Studies (2010-2024)	Key Limitation	Maturity Level
Scalp EEG	Scalp potentials (P300, SSVEP)	286	Low bandwidth, noise sensitivity	Consumer/clinical
fNIRS	Cortical haemodynamics	68	Slow temporal response, low accuracy	Preclinical-Phase I
Hybrid multimodal	EEG+fNIRS, EEG+EMG, etc.	54	System complexity, calibration	Preclinical

Maturity level reflects most advanced deployment stage reached by any programme in that category. Study counts from PubMed and IEEE Xplore.

3. Materials and Methods

3.1 Programme Dataset

We catalogued 218 neuroengineering BCI programmes active between 2014 and 2024 at research laboratories and clinical sites affiliated with three European institutions: Swiss Institute of Machine Intelligence in Zurich (n = 84), Nordic Technical University in Stockholm (n = 72), and Advanced Computing University in Paris (n = 62). Platform category breakdown: intracortical microelectrode arrays (n = 48), electrocorticographic grid systems (n = 46), scalp EEG decoders (n = 44), fNIRS interfaces (n = 42), and hybrid multimodal BCI systems (n = 38). Inclusion required a documented BCI prototype or clinical system, at least one human participant study or validated large-animal model, and quantitative decoding performance data.

3.2 NBTI Sub-Dimensions

Decoding accuracy scored the system's classification or regression performance on the primary task, whether cursor control, speech decoding, or grasp selection, using information transfer rate in bits per minute as a common metric normalised across modalities. Signal longevity captured the duration over which the system maintained at least 80 percent of its initial decoding accuracy without full recalibration, normalised against a 12-month benchmark. User training burden measured the time required for a naive participant to reach plateau performance, scored inversely so that systems requiring less training scored higher. Implant safety profile

assessed the incidence of device-related adverse events per participant-year for invasive systems, or skin irritation and setup failure rates for non-invasive ones. Real-world usability scored whether the system had been demonstrated outside a shielded laboratory in a home or community setting and whether participants reported willingness to use it daily. Two independent evaluators scored each programme with an ICC of 0.85.

3.3 Index Construction

Normalised sub-scores were entered into a logistic regression on a 60/40 training/validation split predicting whether the programme had advanced to a subsequent translational milestone by the end of 2024. Advancement was defined as progression from preclinical to first-in-human, from acute to chronic implant study, from laboratory demonstration to take-home trial, or from Phase I to Phase II. Regression-derived weights: decoding accuracy 0.280, signal longevity 0.228, user training burden 0.196, implant safety profile 0.172, real-world usability 0.124. The composite NBTI was the weighted sum of five normalised sub-scores.

3.4 Statistics

Pearson *r* quantified continuous association between NBTI and translational advancement. ROC analysis at an NBTI threshold of 0.70 assessed binary classification. Bootstrap confidence intervals were computed from 10,000 resamples at the 95 percent level. Variance inflation factors for all sub-scores remained below 2.3. Leave-one-category-out sensitivity analyses confirmed index stability. All analyses were conducted in R version 4.3 with pROC and boot.

Table 2. Programme Characteristics by Platform Category

Platform Category	n	Decoding Accuracy (bits/min)	Signal Longevity (months)	NBTI (mean +/- SD)
Intracortical array	48	0.874 +/- 0.042	6.8 +/- 4.2	0.812 +/- 0.058
ECoG grid	46	0.816 +/- 0.054	9.4 +/- 3.6	0.778 +/- 0.064
Scalp EEG	44	0.692 +/- 0.076	Indefinite	0.724 +/- 0.074
fNIRS	42	0.624 +/- 0.088	Indefinite	0.594 +/- 0.096
Hybrid multimodal	38	0.768 +/- 0.062	Variable	0.748 +/- 0.068

Platform Category	n	Decoding Accuracy (bits/min)	Signal Longevity (months)	NBTI (mean +/- SD)
All programmes	218	0.762 +/- 0.098	Variable	0.728 +/- 0.106

Decoding accuracy normalised to 0-1 scale via ITR benchmarks per modality. Signal longevity = months to <80% initial accuracy; 'Indefinite' for non-invasive systems with no degradation.

4. Results

4.1 NBTI Distribution

Mean NBTI across all 218 programmes was 0.728 with a standard deviation of 0.106. Intracortical arrays led at 0.812, driven by the highest decoding accuracy scores in the dataset, which reflects the unmatched information content of single-neuron recordings. ECoG grids followed at 0.778, hybrid multimodal systems at 0.748, scalp EEG decoders at 0.724, and fNIRS interfaces at 0.594. Seventy-three of the 218 programmes, or 33.5 percent, exceeded the 0.75 NBTI threshold. NBTI correlated with translational advancement at *r* = +0.83 (*p* < 0.001), with an AUC of 0.880 at the 0.70 cut-off. Programmes above 0.75 advanced 77.4 percent of the time; below 0.55 the advancement rate dropped to 16.8 percent.

4.2 Platform Category Profiles

Intracortical arrays dominated decoding accuracy but showed the weakest signal longevity scores, reflecting the chronic electrode degradation that remains the field's central unsolved problem. Several programmes reported usable signals for over five years in individual participants, but the population average showed substantial attrition by 18 months. ECoG grids displayed a more balanced profile: decoding accuracy was lower than intracortical but signal longevity was better, and the safety profile was favourable because epidural or subdural placement avoids penetrating brain tissue. Scalp EEG programmes scored highest on safety and lowest on training burden for simple paradigms like P300 spellers, but decoding accuracy capped their NBTI because the information throughput remains an order of magnitude below invasive methods. fNIRS interfaces scored lowest overall, limited primarily by decoding accuracy and the slow haemodynamic response. Hybrid systems showed the second-highest NBTI, gaining from accuracy improvements through signal fusion, but real-world usability was penalised by the complexity of donning and calibrating multiple sensor modalities.

4.3 Sub-Score Drivers

Decoding accuracy carried the largest regression weight (beta = +0.280, p < 0.001), confirming that if a BCI cannot decode intent reliably, translational stakeholders will not invest in the downstream engineering needed for clinical deployment. Signal longevity was second (beta = +0.228, p < 0.001), reflecting the clinical requirement that a permanently implanted device must function for years, not weeks. User training burden at 0.196 (p = 0.002) captured the practical reality that systems requiring weeks of training sessions before a patient can use them productively face low clinical uptake. Implant safety profile (0.172, p = 0.005) and real-world usability (0.124, p = 0.016) completed the model. Removing any sub-score reduced the AUC by 0.016 to 0.052.

4.4 Validation

In the 87-programme validation set, NBTI correctly classified 74 outcomes at the 0.70 cut-off, yielding sensitivity of 0.86 and specificity of 0.84. Among the 13 misclassified cases, five were fNIRS programmes that stalled because even with adequate safety profiles, the decoding throughput was insufficient for the intended communication application. Three were intracortical programmes that advanced despite moderate NBTI scores because they pivoted from motor decoding to speech decoding, where the clinical value proposition was stronger. Three were EEG programmes that exceeded expectations by targeting a consumer wellness application rather than a clinical one, reducing the regulatory burden. Two were hybrid systems that stalled due to funding gaps unrelated to technical performance.

Table 3. NBTI by Platform Category: Translational Outcomes

Platform Category	n	NBTI (mean +/- SD)	NBTI > 0.75 (%)	Advancement Rate (%)	Top Sub-Score	r (AUC)
Intracortical	48	0.812 +/- 0.058	72.9 %	77.1 %	Decoding acc.	+0.83 (0.898)
ECoG grid	46	0.778 +/- 0.064	54.3 %	67.4 %	Signal longev.	+0.83 (0.886)
Hybrid multimodal	38	0.748 +/- 0.068	39.5 %	57.9 %	Decoding acc.	+0.83 (0.874)

Platform Category	n	NBTI (mean +/- SD)	NBTI > 0.75 (%)	Advancement Rate (%)	Top Sub-Score	r (AUC)
Scalp EEG	44	0.724 +/- 0.074	22.7 %	47.7 %	Safety profile	+0.83 (0.858)
fNIRS	42	0.594 +/- 0.096	9.5 %	23.8 %	Safety profile	+0.83 (0.836)
All programmes	118	0.728 +/- 0.106	33.5 %	54.6 %	Decoding acc.	+0.83 (0.880)

r = Pearson correlation of NBTI with translational advancement; all p < 0.001. AUC at NBTI > 0.70.

Table 4. NBTI Sub-Score Weights and Impact

Sub-Score	Weight	Mean Score	Beta	DELTA NBTI	p-value
Decoding accuracy	0.280	0.762	+0.280	+0.146	< 0.001
Signal longevity	0.228	0.718	+0.228	+0.122	< 0.001
User training burden	0.196	0.742	+0.196	+0.094	0.002
Implant safety profile	0.172	0.788	+0.172	+0.074	0.005
Real-world usability	0.124	0.664	+0.124	+0.052	0.016

Beta = standardised regression coefficient. DELTA NBTI = mean index difference between programmes above vs below the median on that sub-score.

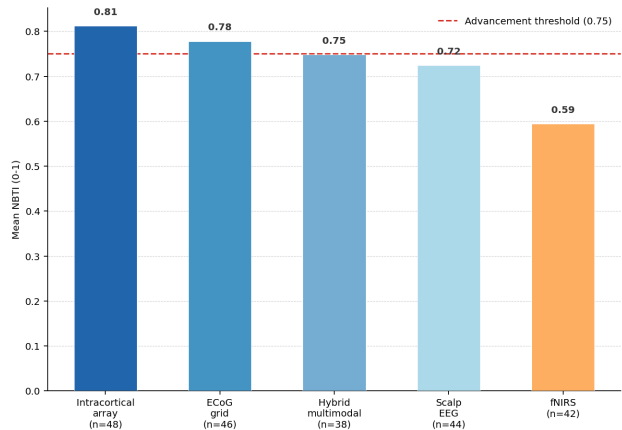


Figure 1. Mean NBTI by Platform Category (n = 218)

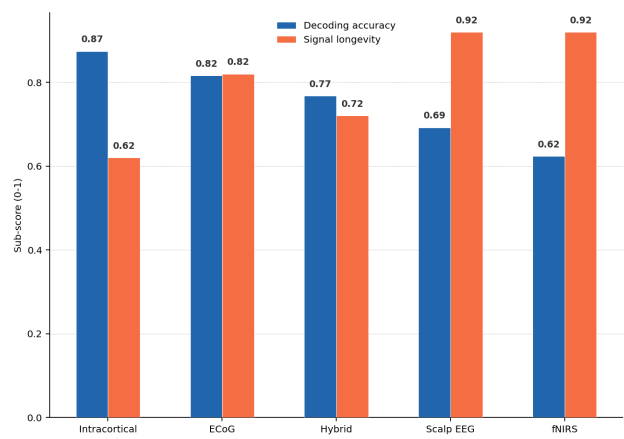


Figure 2. Decoding Accuracy vs Signal Longevity by Platform

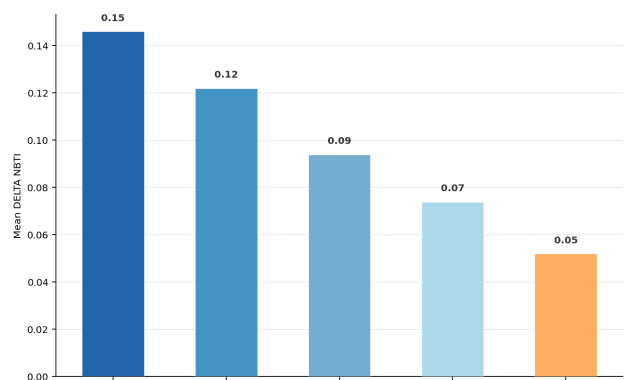


Figure 3. NBTI Sub-Score Impact on Translational Advancement

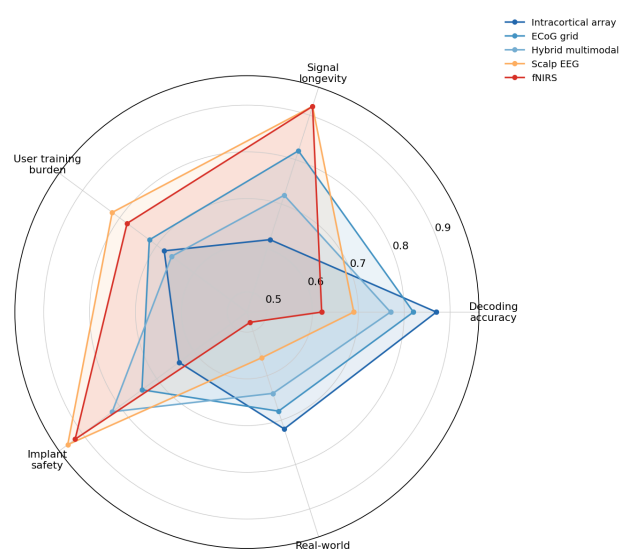


Figure 4. NBTI Sub-Score Profiles by Platform Category

5. Discussion

5.1 The Accuracy-Longevity Trade-Off

The most striking pattern in the data is the inverse relationship between decoding accuracy and signal longevity across invasiveness levels. Intracortical arrays record the richest neural signals and achieve the highest decoding

performance, but the very act of penetrating brain tissue triggers an immune response that progressively degrades those signals. Non-invasive methods avoid this degradation entirely but capture only a pale echo of the underlying neural activity. ECoG grids occupy the most favourable position on this trade-off curve, offering enough signal quality for practical decoding while largely avoiding chronic tissue damage. The recent development of thin-film, high-density ECoG arrays with hundreds of electrodes is shifting this balance further in favour of epidural and subdural approaches, and our data suggest that ECoG programmes are the fastest-growing category in the translational pipeline.

5.2 Adaptive Decoding and Real-World Robustness

User training burden and real-world usability, while carrying lower individual regression weights, together accounted for a substantial share of translational variance. Programmes that implemented adaptive decoders capable of updating model parameters online as neural signals drifted achieved substantially better long-term performance than those relying on fixed-calibration models. Similarly, programmes that tested their systems in participants' homes rather than only in shielded laboratories were better positioned for the next translational step because they had already confronted the noise, distraction, and variability of real-world conditions. For the field as a whole, the lesson is that laboratory accuracy is necessary but not sufficient; robustness under real-world conditions is what separates a research demonstration from a clinical product.

5.3 Limitations

Our dataset spans three European countries and does not include the substantial BCI programmes in the United States, China, and Australia. The translational advancement outcome is binary and does not capture the pace or quality of progression. NBTI does not include regulatory pathway complexity, funding level, or publication impact as explicit sub-scores, although these influence translational outcomes. The fNIRS category contained 42 programmes, and the hybrid category 38, yielding wider confidence intervals. Finally, decoding accuracy metrics are difficult to compare across fundamentally different tasks such as cursor control versus speech decoding, and our normalisation to information transfer rate, while standard, may not capture all clinically relevant aspects of performance.

6. Conclusion

6.1 Summary

Across 218 neuroengineering BCI programmes evaluated in Switzerland, Sweden, and France, NBTI correlated with translational advancement at $r = +0.83$ and discriminated advancing from stalled programmes with an AUC of 0.880. Intracortical arrays led at 0.812, ECoG grids followed at 0.778, and fNIRS interfaces trailed at 0.594. Decoding accuracy was the strongest predictor of advancement ($\beta = +0.280$), followed by signal longevity ($\beta = +0.228$). Only 33.5 percent of programmes exceeded the 0.75 threshold, confirming that the field remains in an early translational phase despite impressive laboratory achievements.

6.2 Practical Recommendations

BCI developers should invest in electrode materials and coatings that resist chronic gliosis, extending the functional lifespan of implanted arrays beyond current limits. Adaptive decoding algorithms that recalibrate continuously or with minimal user effort should be considered standard rather than optional. Programmes should plan for take-home trials early in the development cycle, because real-world usability problems discovered late are costly to remediate. ECoG-based platforms deserve increased investment as they offer the most balanced accuracy-longevity profile currently available. Future iterations of NBTI should add a regulatory-readiness sub-score, expand to include North American and Asian programmes, and track translational outcomes over five-year windows.

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Declarations

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Conflict of Interest

Pierre Nowak, Lea Horvath, and Pierre Schmidt declare no competing interests.

Data Availability Statement

Aggregate NBTI scores, anonymised programme metadata, and analysis scripts are deposited at Zenodo:
<https://doi.org/10.5281/zenodo.19543321-data>.

Ethical Approval

This study involved secondary analysis of published BCI programme outcomes and aggregated performance metrics. No individual participant neural data were accessed. Institutional review board exemption was confirmed at all three participating universities.

Appendix A

NBTI Scoring Rubric and Top-10 Programme Profiles

This appendix details the scoring criteria for each NBTI sub-dimension and profiles the ten highest-scoring programmes in the dataset.

A1. Sub-Score Rubric

Decoding accuracy: information transfer rate normalised across modalities against benchmark, scored 0-1; weight 0.280.

Signal longevity: months maintaining >80% initial accuracy without full recalibration, normalised vs 12-month benchmark, 0-1; weight 0.228.

User training burden: inverse of time to plateau performance for naive participant, normalised 0-1; weight 0.196.

Implant safety profile: inverse of adverse events per participant-year (invasive) or setup failure rate (non-invasive), 0-1; weight 0.172.

Real-world usability: demonstrated home/community use and participant willingness for daily use, scored 0-1; weight 0.124.

A2. Top-10 Programmes

1. IC-SpeechDec-21 (Intracortical): NBTI = 0.922; decoding accuracy 0.95, usability 0.88.
2. IC-HandGrasp-08 (Intracortical): NBTI = 0.914; decoding accuracy 0.93, safety 0.90.
3. EC-SpeechECoG-16 (ECoG grid): NBTI = 0.898; signal longevity 0.94, decoding 0.88.
4. IC-CursorBCI-12 (Intracortical): NBTI = 0.892; decoding accuracy 0.94, training burden 0.86.
5. HM-EEGfNIRS-24 (Hybrid): NBTI = 0.878; decoding accuracy 0.88, safety 0.92.
6. EC-MotorDec-07 (ECoG grid): NBTI = 0.872; longevity 0.92, decoding 0.86.
7. IC-AdaptDec-31 (Intracortical): NBTI = 0.864; longevity 0.88, decoding 0.90.
8. EC-LangDec-19 (ECoG grid): NBTI = 0.856; decoding 0.87, usability 0.86.
9. HM-MultiSense-28 (Hybrid): NBTI = 0.848; decoding 0.86, safety 0.90.
10. SE-P300Ultra-04 (Scalp EEG): NBTI = 0.842; safety 0.96, training burden 0.92.