AI tools for analysis of empirical experiments on economic behavior

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Abstract: This paper introduces a methodological framework designed to democratize neuroeconomics by integrating 4-channel EEG hardware (Muse 2) with advanced computational workflows. The central thesis argues for a transition from static, linear feature extraction to dynamic, spatio-temporal modeling to capture the evolving cognitive processes of economic decision-making. By leveraging the "NeuroSense" pipeline—utilizing the meegkit library for robust ringing artifact reduction—researchers can maintain high signal integrity from portable, dry-electrode devices.

The core of the framework utilizes the "NeuCube" Spiking Neural Network (SNN) architecture, which employs biologically plausible learning rules like Spike-Timing-Dependent Plasticity (STDP). This architecture effectively upgrades sparse surface data into a 3D evolving brain model, allowing for the reconstruction of complex neural states. The utility of this unified pipeline is demonstrated through three canonical economic paradigms: Willingness to Pay (WTP), the Ultimatum Game (UG), and Frontal Alpha Asymmetry (FAA). This approach enhances the ecological validity of neuroeconomic research, enabling rigorous "in-the-wild" experiments in real-world economics.

Keywords: neuroeconomics, economic behavior, AI workflow, brain spikes

JEL: M10, D87, D91

1. INTRODUCTION

The field of empirical economics has long relied on behavioral observation and self-reported preferences to construct models of human decision-making. However, the "revealed preference" paradigm is increasingly being supplemented, and in some cases challenged, by the "measured biological state" paradigm offered by neuroeconomics. We stand at a critical juncture where the technological barriers to entry for high-fidelity neuroimaging are collapsing, coincident with a revolution in artificial intelligence capable of decoding the complex, non-linear dynamics of the human brain. This report outlines a methodological framework that integrates low-cost, sparse-channel electroencephalography (EEG)—specifically the Muse 2 headband—with advanced computational workflows derived from the "NeuroSense" project (Colafiglio et al., 2024) and the "NeuCube" Spiking Neural Network (SNN) architecture (Kasabov, 2014).

The central thesis of this proposed outlook is that the analysis of economic behaviors—ranging from Willingness to Pay (WTP) calculations to cooperative strategies in the Ultimatum Game—requires a transition from static, linear feature extraction to dynamic, spatio-temporal modeling (Kasabov, 2014). Economic decisions are not instantaneous, isolated events; they are evolving cognitive processes characterized by temporal fluctuations in attention, valuation, and executive control (Ramsøy et al., 2018). Traditional analytical methods, such as event-related potential (ERP) averaging or Fourier-based power spectral density (PSD) analysis, often average out the granular temporal dynamics that contain the "why" behind a decision. Furthermore, the reliance on expensive, high-density EEG rigs has restricted neuroeconomic research to artificial laboratory settings, limiting the ecological validity of the findings (Cann et al., 2024).

By leveraging the "NeuroSense" pipeline, which utilizes the meegkit Python library for robust artifact management (Colafiglio et al., 2024; Barachant, n.d.), and coupling it with the biologically plausible NeuCube SNN architecture (Kasabov, 2014), researchers can theoretically map sparse data from portable devices into a 3D evolving brain model. This integration promises to democratize neuroeconomics, allowing for "in-the-wild" experiments on consumer choice and risk assessment while maintaining the analytical rigor required for scientific publication. This report details the hardware capabilities, the preprocessing algorithms, the neuromorphic modeling architecture, and the specific application of this unified framework to canonical economic experimental paradigms.

2. THE HARDWARE SUBSTRATE: DEMOCRATIZING DATA ACQUISITION WITH MUSE 2

The selection of the Muse 2 headband as the primary data acquisition instrument for this proposed framework is driven by a strategic necessity to balance signal fidelity with ecological accessibility. In the context of economic experiments—where subject comfort and naturalistic behavior are paramount—the intrusive nature of traditional 64-channel wet-cap systems acts as a confounder, potentially altering the very decision-making processes researchers aim to study. The Muse 2, a consumer-grade device, offers a non-invasive alternative, but its utilization in rigorous scientific inquiry necessitates a deep understanding of its technical specifications and limitations.

2.1. Sensor Topology and Technical Specifications

The Muse 2 employs a sparse electrode configuration consisting of four active channels: AF7 and AF8 (positioned over the forehead) and TP9 and TP10 (positioned behind the ears, over the mastoids) (InteraXon, 2023). These locations are defined according to the International 10-20 System for electrode placement, ensuring that data is spatially standardized against the broader neuroimaging literature. The device also utilizes a reference electrode located at Fpz, which is critical for establishing a common mode rejection ratio sufficient to isolate neural signals from environmental electrical noise.

The placement of these four sensors is serendipitously aligned with two primary neural circuits involved in economic behavior. The frontal electrodes (AF7, AF8) provide coverage of the dorsal and ventral prefrontal cortex, regions heavily implicated in executive control, value encoding, and the regulation of impulsive behavior. The temporal electrodes (TP9, TP10) sit adjacent to the temporal lobes, regions associated with auditory processing, semantic memory retrieval, and emotional integration (InteraXon, 2023). This topology allows the Muse 2 to capture the interaction between "top-down" control mechanisms (frontal) and "bottom-up" sensory or emotional inputs (temporal), a dynamic central to theories of bounded rationality in economics.

Table 1 - The Muse 2 specification table

Specification	Value	Neuroeconomic Implication
Channels	4 (AF7, AF8, TP9, TP10)	Limits spatial resolution; necessitates sparse encoding algorithms.
Sampling Rate	256 Hz	Sufficient for Delta, Theta, Alpha, Beta; captures lower Gamma.
ADC Resolution	12-bit (16-bit internal)	Provides adequate dynamic range for detecting ERP components like N400.
Electrode Type	Conductive Gold/Silver	Dry electrodes increase susceptibility to impedance instability and motion artifacts.
Communication	Bluetooth Low Energy (BLE)	Enables wireless, untethered experiments in retail or social settings.

2.2. Empirical Validation of Sparse EEG

A primary objective of the proposed article is to preemptively address skepticism regarding the validity of "sparse EEG." The report must synthesize recent findings that demonstrate the Muse 2’s capability to replicate canonical neurophysiological effects. Notably, research has confirmed that the Muse 2 can reliably detect the N400 Event-Related Potential (ERP) (Cann et al., 2024; Krigolson et al., 2017). The N400 is a negative-going voltage deflection that peaks approximately 400 milliseconds after the onset of a stimulus and is traditionally associated with semantic incongruity. In economic contexts, the N400 is a vital marker for detecting "violations of expectation," such as encountering an unreasonably high price or an unfair offer in a negotiation.

Furthermore, comparative studies using the Muse 2 alongside research-grade systems (like the actiCHamp) have shown that despite the lower channel count, the device accurately captures broad spectral features—specifically Alpha (7.5-13 Hz) and Beta (13-30 Hz) power—which are the standard metrics for calculating Frontal Alpha Asymmetry (FAA), a proxy for approach/avoidance motivation (Cann et al., 2024; Smith et al., 2017). The device’s ability to resolve the N400 effect with adequate internal consistency suggests that, when coupled with appropriate signal processing, the lack of spatial density does not preclude the measurement of precise temporal cognitive events.

2.3. The "Sparse Data" Challenge and the AI Solution

While the Muse 2 provides a valid signal, the paucity of channels presents a fundamental challenge for source localization. Traditional inverse problems (e.g., LORETA) are ill-posed with only four data points. This constraint necessitates a shift in analytical strategy: from spatial localization to temporal-dynamic modeling. The outlook paper will argue that Artificial Intelligence—specifically Spiking Neural Networks (SNNs)—offers the solution to this "sparse data problem" (Kasabov, 2014).

Instead of attempting to triangulate the exact physical source of a signal (which is mathematically impossible with high precision using 4 sensors), the proposed NeuCube workflow uses the available sensors as input nodes to stimulate a high-dimensional, virtual brain model. The AI learns to map the temporal structure of the input—the precise timing relationships between frontal and temporal firing rates—to varying cognitive states. Thus, the hardware provides the accessibility, while the software (NeuroSense and NeuCube) provides the necessary dimensionality expansion, effectively "reconstructing" the complexity of the underlying neural state from the limited surface projections.

3. THE NEUROSENSE PREPROCESSING FRAMEWORK: ENSURING SIGNAL INTEGRITY

The adage "garbage in, garbage out" is particularly pertinent to dry-electrode EEG. Without a rigorous preprocessing pipeline, the data from Muse 2 is often dominated by oculomotor artifacts (blinks), electromyogenic noise (jaw clenches), and environmental interference. The "NeuroSense" project establishes a standardized workflow for cleaning sparse EEG data that is critical for subsequent AI analysis (Colafiglio et al., 2024).

3.1. The Megkit Ecosystem and Artifact Management

The core of the NeuroSense preprocessing pipeline is the integration of the meegkit Python library, a specialized toolkit for EEG and MEG denoising (Colafiglio et al., 2024). Standard filtering techniques, such as applying a simple Butterworth bandpass filter, often fail in the presence of high-amplitude transient artifacts common to mobile EEG. When a large spike (e.g., a sudden electrode disconnect or a strong jaw clench) passes through a standard filter, it creates "ringing" artifacts—artificial oscillations that ripple out from the transient event. These ripples can easily be mistaken for neural oscillations (like Theta bursts) by downstream machine learning algorithms, leading to false positives in economic decision detection.

The NeuroSense protocol employs a sophisticated **Ringing Artifact Reduction** technique provided by meegkit (Colafiglio et al., 2024; de Cheveigné and Arzounian, 2018):

1. **Outlier Detection:** The pipeline first identifies artifactual intervals by treating them as statistical outliers relative to the standard distribution of the EEG signal. This is achieved using a K-Nearest Neighbors (K-NN) algorithm with a contamination hyperparameter, typically tuned to 0.1. The K-NN approach is robust because it does not rely on simple amplitude thresholds, which can vary across subjects, but rather on the local density of the signal data points.
2. **Artifact Interpolation:** Once an interval is flagged as an artifact, the meegkit algorithm does not merely zero it out (which would create a discontinuity). Instead, it estimates the impulse response of the filter associated with the artifact and subtracts it, or interpolates the interval using samples from the surrounding valid trial data. This effectively "inpaints" the corrupted segment, preserving the spectral continuity of the data without introducing the phase distortions associated with filter ringing.

3.2. Time-Sliding Estimation for Dynamic Analysis

Economic behavior is rarely stationary. The cognitive state of a subject evaluating a gamble changes millisecond by millisecond—from visual perception to value integration to motor preparation. The NeuroSense framework addresses this by eschewing static epoching in favor of Time-Sliding Estimation (Colafiglio et al., 2024).

This method involves segmenting the cleaned continuous EEG data into overlapping sub-epochs (e.g., 1-second windows with 50% overlap, or 5-second windows for longer tasks). This sliding window approach generates a continuous trajectory of feature vectors, allowing researchers to track the evolution of emotional and cognitive metrics over time. For an economic experiment, this is crucial. It differentiates the anticipation of a reward from the consumption of it. The NeuroSense pipeline extracts features (such as Power Spectral Density or Differential Entropy) from each of these sliding windows, creating a time-resolved dataset that captures the dynamic nature of the decision-making process.

3.3. Implementation in Python: The MNE Standard

To ensure reproducibility and standardization, the NeuroSense workflow relies heavily on the Python ecosystem, specifically the MNE-Python library (Gramfort et al., 2013). After artifact reduction via meegkit, the data is resized, restructured, and encapsulated into MNE EpochsArray objects. This encapsulation is vital for maintaining data consistency, as it preserves channel names (AF7, AF8, TP9, TP10), sampling rates, and sensor types within a standardized metadata structure (Colafiglio et al., 2024).

Proposed Preprocessing Algorithm:

Data Ingestion: Load raw Muse 2 data (CSV/XDF) and convert to MNE Raw objects.

Line Noise Removal: Apply ZapLine or notch filters (50/60Hz) to remove power grid interference.

Global Detrending: Use Robust Detrending from meegkit to remove slow drifts caused by sweat or movement (de Cheveigné and Arzounian, 2018).

Artifact Detection (K-NN): Train K-NN on the detrended data to identify high-variance outliers (contamination ~ 0.1).

Ringing Reduction: Apply meegkit.reduce_ringing to the identified intervals.

Segmentation: Apply time-sliding windows keyed to experimental triggers (e.g., stimulus onset).

Standardization: Output MNE Epochs ready for NeuCube encoding.

4. THE NEUCUBE ARCHITECTURE: SPIKING NEURAL NETWORKS FOR SPATIO-TEMPORAL MODELING

While NeuroSense provides the mechanism for data hygiene, the NeuCube architecture provides the analytical engine. The proposed journal article will argue that Spiking Neural Networks (SNNs) represent a superior modality for neuroeconomic analysis compared to traditional Artificial Neural Networks (ANNs) or Support Vector Machines (SVMs), primarily due to their biological plausibility and their inherent capacity to process temporal information (Kasabov, 2014).

4.1. Theoretical Foundation: Spiking Information Processing

The human brain does not encode information in static floating-point numbers; it uses discrete events called spikes. The timing of these spikes—the precise latency between a presynaptic and postsynaptic potential—encodes rich information about the strength and causality of a stimulus. Traditional machine learning models (like MLPs or CNNs) typically use rate-based coding, where neuronal activity is averaged over time, discarding this fine-grained temporal structure.

NeuCube is built upon the principles of Spiking Information Processing (Kasabov, 2014). It utilizes models of neurons (typically Leaky Integrate-and-Fire or LIF models) that accumulate membrane potential over time and fire only when a threshold is reached. This event-driven nature allows NeuCube to model the trajectories of brain activity. In the context of an economic decision, the SNN can distinguish between a rapid, intuitive choice (fast spike train propagation) and a deliberative, conflicted choice (delayed, oscillatory spike patterns), even if the aggregate energy (Alpha power) appears similar in a standard analysis.

4.2. The 3D SNN Cube: Mapping and Reservoir Computing

The defining feature of the NeuCube architecture is its 3D structural mapping. The model consists of a three-dimensional lattice of spiking neurons, arranged to approximate the spatial geometry of the brain (e.g., using Talairach or MNI coordinates) (Kasabov, 2014). This structure serves as a "reservoir"—a complex dynamical system that projects low-dimensional inputs into a high-dimensional state space.

The Mapping of Sparse Data:

The outlook paper must address how a 4-channel device utilizes a 3D volume. In the NeuCube framework, the Muse 2 electrodes (AF7, AF8, TP9, TP10) are mapped to their corresponding coordinates on the surface of the virtual brain cube (Kasabov, 2014). These nodes act as injection points. When the Muse detects a signal, the corresponding input neurons in the cube fire, sending spike trains propagating through the lattice via recurrent lateral connections.

This propagation activates "hidden" neurons within the cube that correspond to internal brain structures not directly measured by the surface electrodes. Through this process, the SNN effectively "inflates" the sparse data, generating a volumetric representation of brain activity based on the learned connectivity patterns. The sparse input stimulates a polychronous wave of activity—a reproducible time-locked pattern of firing—that represents the cognitive state (e.g., "Risk Aversion").

4.3. Evolutionary Learning: STDP and deSNN

NeuCube employs Spike-Timing-Dependent Plasticity (STDP) as its unsupervised learning rule (Kasabov, 2014). STDP is a biological learning mechanism where the strength of a synapse is adjusted based on the relative timing of pre- and post-synaptic spikes. If neuron A spikes milliseconds before neuron B, the connection is strengthened (Long-Term Potentiation); if the reverse occurs, it is weakened (Long-Term Depression).

This allows the NeuCube to learn causal relationships in the EEG data without explicit labeling. For example, if activity in the temporal sensors (TP9/10, memory) consistently precedes activity in the frontal sensors (AF7/8, decision) during a "Buy" decision, the SNN will autonomously strengthen the connections representing this pathway.

For classification, the model uses a Dynamic Evolving SNN (deSNN) classifier attached to the output of the cube. The deSNN is trained in a supervised manner to associate the dynamic state of the reservoir (the polychronous wave) with a specific label (e.g., "High WTP" vs. "Low WTP"). Empirical studies have shown that this architecture achieves superior accuracy to LSTMs and SVMs on EEG data, with accuracies reaching 96-97% in some pattern recognition tasks (Kasabov, 2014; Doborjeh et al., 2017).

5. SYNERGISTIC WORKFLOW FOR EMPIRICAL ECONOMIC EXPERIMENTS

The primary contribution of the proposed article is the synthesis of the hardware (Muse 2), the preprocessing (NeuroSense), and the modeling (NeuCube) into a cohesive research workflow. This section outlines how this pipeline is applied to three specific economic paradigms: Willingness to Pay, the Ultimatum Game, and Frontal Alpha Asymmetry.

5.1. Case Study A: Willingness to Pay (WTP)

Cognitive Theory: WTP is a measure of the subjective value a consumer assigns to a good. It involves a complex integration of visual perception, memory (pricing norms), and emotional valuation. Standard methods rely on self-reports, which are biased by social desirability.

Neural Markers: Research indicates that prefrontal Gamma asymmetry (30-44 Hz) is strongly coupled with the actual decision phase of WTP calculations (Ramsøy et al., 2018).

Proposed Workflow:

1. **Protocol:** Subjects wear the Muse 2 and view product images for 3-5 seconds, followed by a decision prompt to enter a price.
2. **Preprocessing:** NeuroSense removes the inevitable eye-movement artifacts associated with visual scanning of the product.
3. **NeuCube Modeling:** The SNN is trained on the epoch from 200ms to 800ms post-stimulus. The input encoding is tuned to be sensitive to high-frequency bursts (Gamma).
4. **Insight Generation:** Instead of simply correlating average Gamma power with price, the NeuCube identifies the latency of the valuation signal. The hypothesis to be tested is that high-certainty valuations (high WTP) are characterized by a faster formation of a stable "attractor state" in the frontal region of the SNN Cube compared to ambivalent valuations. The SNN's ability to model temporal trajectories makes it uniquely suited to test this "speed-of-valuation" hypothesis.

5.2. Case Study B: The Ultimatum Game (UG)

Cognitive Theory: The UG assesses responses to fairness. A Proposer offers a split of money; the Responder accepts or rejects. Rejection of "unfair" offers (e.g., 90/10 split) is often driven by negative emotional arousal (anger/disgust).

Neural Markers: The N400 and Feedback Related Negativity (FRN) are critical markers. An unfair offer elicits a negativity that reflects a violation of social norms (semantic incongruity).

Proposed Workflow:

1. **Protocol:** Subjects play a computerized UG while EEG is recorded.
2. **Preprocessing:** The ringing artifact reduction is critical here to preserve the morphology of the N400 ERP, which is a low-frequency, transient waveform.
3. **NeuCube Modeling**: The 4-channel data is mapped to the 3D Cube. The STDP rule allows the network to learn the specific spatio-temporal pattern of "social violation."
4. **Insight Generation:** The paper will propose using the SNN to model the adaptation of fairness norms. Does the neural response to an unfair offer change after 20 trials? The "evolving" nature of the NeuCube (which has long-term memory via synaptic weight changes) allows it to track this plasticity, offering a dynamic view of how economic norms are learned and updated in real-time.

5.3. Case Study C: Frontal Alpha Asymmetry (FAA)

Cognitive Theory: FAA is the most widely used metric in consumer neuroscience, serving as a proxy for motivation (Left = Approach, Right = Avoidance/Withdrawal) (Smith et al., 2017).

The Metric: Standard calculation: $FAA = ln(Alpha_{Right}) - ln(Alpha_{Left})$ (using AF8 and AF7) (Harmon-Jones, 2003).

The Critique: The literature on FAA is inconsistent, with many studies failing to find robust correlations with behavior. This is likely because the simple linear subtraction ignores the complex, non-linear interactions between hemispheres.

Proposed Workflow:

1. **Protocol:** Subjects view advertisements or potential investments.
2. **NeuCube Solution:** Instead of calculating a difference score, the raw Alpha streams from AF7 and AF8 are fed into the SNN**.**
3. **Insight Generation:** The SNN models the synchrony and information transfer between the left and right frontal lobes. It may reveal that "Approach" is not just about more left activity, but about a specific phase-locking relationship or a specific temporal sequence of activation between the hemispheres. By moving from a linear metric (FAA) to a non-linear dynamic model (SNN), the paper argues that the predictive power of frontal asymmetry can be significantly enhanced.

6. TECHNICAL IMPLEMENTATION & REPRODUCIBILITY

The scientific article must emphasize that this workflow is not theoretical but currently implementable using open-source tools.

Python Implementation Ecosystem

The integration relies on a Python-based stack. The meegkit library (Barachant, n.d.) handles the denoising, providing the "Ringing Artifact Reduction" class. MNE-Python (Gramfort et al., 2013) provides the data structures (Epochs, Evoked) and visualization tools for sensor-space analysis. NeuCube-Py (KEDRI, 2021) or the Java-based NeuCube software provides the SNN modeling capabilities.

Table 2 - Python Implementation Ecosystem

Stage	Tool	Language	Function
Ingestion	MuseLSL/Mind Monitor	Python	Stream capture & XDF formatting
Denoising	meegkit	Python	Robust Detrending, Ringing Artifact Reduction
Formatting	MNE-Python	Python	Epoching, Filtering (ZapLine), Metadata management
Encoding	NeuCube/NeuCube-Py	Java/Python	Spike encoding (Threshold/Ben's Spiker Algorithm)
Modeling	NeuCube	Java/Python	3D Mapping, STDP Learning, Visualization
Classification	scikit-learn/NeuCube	Python	SVM (baseline) or deSNN (neuromorphic)

Reproducibility and Open Science

The report advocates for the release of datasets similar to "NeuroSense" (Colafiglio et al., 2024)—datasets that include both the raw Muse data and the behavioral labels (e.g., WTP values, UG decisions). The NeuroSense dataset serves as a benchmark, demonstrating that even with low-cost hardware, high-quality, reusable data can be generated if the preprocessing protocols are strictly adhered to.

7. STRATEGIC CONCLUSIONS AND FUTURE OUTLOOK

The convergence of consumer-grade EEG and neuromorphic computing represents a paradigm shift for neuroeconomics. The outlook paper concludes that the limitations of sparse hardware (Muse 2) are not fatal flaws but rather engineering constraints that can be overcome—and in some ways leveraged—through advanced AI.

From State to Trajectory: The shift from analyzing static brain states (e.g., "High Alpha") to dynamic neural trajectories (e.g., "Polychronous wave A") allows for a more granular understanding of the cognitive processes underlying economic choice. The NeuCube architecture is the key enabler of this shift, providing a biologically plausible method to decode the timing of value and risk computations.

Ecological Validity: The validation of the NeuroSense pipeline for artifact removal means that economic experiments can move out of the Faraday cage. We can now envision studies analyzing the neural correlates of "buyer's remorse" in a real retail environment or the stress of "loss aversion" on a trading floor.

The "Glass Box" AI: Unlike deep learning models which often act as black boxes, the NeuCube architecture offers interpretability. The ability to visualize the connections formed within the 3D cube provides researchers with "explainable AI," offering insights into the functional connectivity changes that drive behavioral differences (Kasabov, 2014).

In summary, the current paper delineates a rigorous, technically sound, and theoretically rich pathway for utilizing AI tools to unlock the potential of empirical economic experiments. By rigorous application of the NeuroSense preprocessing standards and the NeuCube modeling framework, the community can transform low-cost EEG from a novelty into a serious instrument of scientific discovery..

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References

1. Barachant, A. (n.d.) meegkit: EEG and MEG denoising in Python. Available at: https://github.com/nbara/python-meegkit (Accessed: 24 May 2024).
2. Cann, R., Tenison, C. and McCarty, C. (2024) 'Exploring the Utility of the Muse Headset for Capturing the N400: Dependability and Single-Trial Analysis', Sensors, 24(24), p. 7961.
3. Colafiglio, T., Lombardi, A., Sorino, P., Brattico, E., Lofù, D., Danese, D., Di Sciascio, E., Di Noia, T. and Narducci, F. (2024) 'NeuroSense: A Novel EEG Dataset Utilizing Low-Cost, Sparse Electrode Devices for Emotion Exploration', IEEE Access, 12, pp. 159296-159315. doi: 10.1109/ACCESS.2024.3487932.
4. de Cheveigné, A. and Arzounian, D. (2018) 'Robust detrending, rereferencing, outlier detection, and inpainting for multichannel data', NeuroImage, 172, pp. 903-912.
5. Doborjeh, M.G., Capecci, E. and Kasabov, N. (2017) 'Classification and segmentation of fMRI Spatio-Temporal Brain Data with a NeuCube evolving Spiking Neural Network model', IEEE Symposium on Evolving and Autonomous Learning Systems.
6. Gramfort, A., Luessi, M., Larson, E., Engemann, D.A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L. and Hämäläinen, M. (2013) 'MEG and EEG data analysis with MNE-Python', Frontiers in Neuroscience, 7(267).
7. Harmon-Jones, E. (2003) 'Clarifying the emotive functions of asymmetrical frontal cortical activity', Psychophysiology, 40(6), pp. 838-848.
8. InteraXon (2023) Muse 2 Technical Specifications. Available at: https://choosemuse.com (Accessed: 24 May 2024).
9. Kasabov, N.K. (2014) 'NeuCube: A spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data', Neural Networks, 52, pp. 62–76. doi: 10.1016/j.neunet.2014.01.006.
10. KEDRI (2021) NeuCube-Py: Python implementation of the NeuCube architecture. Available at: https://github.com/KEDRI-AUT/NeuCube-Py (Accessed: 24 May 2024).
11. Krigolson, O.E., Williams, C.C., Norton, A., Hassall, C.D. and Colino, F.L. (2017) 'Choosing Muse: Validation of a Low-Cost, Portable EEG System for ERP Research', Frontiers in Neuroscience, 11, p. 109.
12. Ramsøy, T.Z., Skov, M., Christensen, M.K. and Stahlhut, C. (2018) 'Frontal Brain Asymmetry and Willingness to Pay', Frontiers in Neuroscience, 12, p. 138.
13. Smith, E.E., Reznik, S.J., Stewart, J.L. and Allen, J.J.B. (2017) 'Assessing and conceptualizing frontal EEG asymmetry: An updated primer on recording, processing, analyzing, and interpreting', International Journal of Psychophysiology, 111, pp. 98-114.