FROM SIGNAL GENERATION TO REACTION ANALYSIS: A REVIEW OF SOFTWARE TOOLS AND AI MODELS IN AUDIO STIMULATION RESEARCH

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Abstract. Audio stimulation has emerged as a valuable methodology across clinical neuroscience, cognitive research, and human-computer interaction, driving demand for dedicated software tools capable of delivering precise stimuli and capturing human responses. This paper reviews existing platforms, tools, and AI models relevant to audio stimulation research, examining their design approaches, core capabilities, and limitations in supporting end-to-end experimental workflows. A survey of prominent tools reveals clear functional fragmentation across the field. Stimulus delivery platforms such as PsychoPy [1] and OpenSesame [2] provide precise, programmable audio and visual stimulus presentation with basic response logging, but offer no intelligent reaction analysis. Biosignal feedback tools such as BrainBay [3] enable real-time processing and threshold-based neurofeedback from EEG and physiological signals, but lack structured audio stimulus generation. Adaptive paradigm frameworks such as BART [4] support real-time physiologically-triggered stimulation, yet remain confined to fMRI environments with no machine learning component. A new generation of AI foundation models including ZUNA [5], focused on EEG signal quality reconstruction, and NeuroLM [6], a multi-task framework for EEG classification demonstrate the growing maturity of machine learning approaches to brain signal analysis, but operate entirely independently of any stimulation pipeline. This review identifies a clear and unaddressed research gap: no existing platform integrates programmable audio signal generation with automated, machine learning-driven reaction analysis within a single unified environment. A unified platform spanning stimulus design, biosignal acquisition, and intelligent reaction analysis would represent a significant advancement for both experimental neuroscience and applied brain-computer interface research.

Keywords: *audio stimulation, neurofeedback, electroencephalography, brain-computer interface, machine learning, signal processing, experimental neuroscience*

Introduction

Audio stimulation has long served as a fundamental tool in neuroscientific investigation. From early auditory evoked potential experiments to contemporary brain-computer interface paradigms which have evolved from basic communication aids [10] to sophisticated systems requiring real-time ML inference, researchers depend on systems that can generate customisable stimuli, synchronise them with biosignal acquisition hardware, and apply intelligent analysis to captured responses, ideally within a single coherent workflow.

The current software landscape is characterised by pronounced functional fragmentation. Stimulus delivery platforms such as PsychoPy [1] and OpenSesame [2] are fundamentally stimulus-presentation tools with no capacity for physiological response analysis. Biosignal tools such as BrainBay [3] offer neurofeedback but cannot generate structured stimuli. Adaptive frameworks such as BART [4] introduce closed-loop stimulation but remain coupled to fMRI. AI foundation models such as ZUNA [5] and NeuroLM [6] are transforming brain signal analysis yet exist in isolation from stimulation infrastructure. This fragmentation forces researchers to assemble ad hoc pipelines from incompatible tools, limiting reproducibility and precluding real-time closed-loop paradigms.

This paper addresses this fragmentation through a systematic review guided by three questions:

- What tools and AI models currently support audio stimulation research?
- What functional gaps exist when these tools are evaluated as an end-to-end workflow?
- What architectural requirements would a unified platform need?

This paper contributes a structured taxonomy of six pivotal tools and a comparative evaluation that delineates the functional disconnects currently hindering end-to-end experimental workflows.

Background and Related Works

Audio stimulation encompasses techniques in which acoustic signals elicit measurable neural, physiological, or behavioural responses, from auditory evoked potentials (AEPs) and steady-state responses (ASSRs) to oddball and binaural beat paradigms. Applications span tinnitus therapy, auditory rehabilitation, and BCI research, all requiring high temporal precision and synchronisation between stimuli and biosignal recording.

Experiments follow a three-stage pipeline:

- Stimulus design and generation

- Biosignal acquisition synchronised with stimulus markers
- Response analysis.

Machine learning for EEG has accelerated rapidly, with compact architectures such as EEGNet [9] demonstrating that convolutional neural networks can generalise across BCI paradigms, and the recent emergence of large-scale foundation models representing a further qualitative advance. Closed-loop neurofeedback, recognised as a paradigm requiring tight integration between signal decoding and stimulus adaptation [11], exemplifies the workflow that current fragmented tools fail to support natively. Platforms such as BCILAB [12] represented an early attempt at integrating signal processing with ML classification within MATLAB, yet remained disconnected from stimulus generation and lacked support for modern foundation models. Prior reviews have addressed timing accuracy [7, 8] and deep learning for EEG classification separately, but none jointly examines stimulus delivery, biosignal tools, adaptive frameworks, and AI models to identify integration gaps.

Methodology

The review was conducted through search of IEEE Xplore, PubMed, Google Scholar, ACM Digital Library, and arXiv, prioritising publications from 2010–2026 and supplemented by GitHub repositories and technical reports. Tools were included if they address at least one pipeline stage and are supported by published documentation. Six tools are reviewed across four categories:

- Stimulus Delivery Platforms
- Biosignal Feedback Tools
- Adaptive Paradigm Frameworks
- AI Foundation Models for EEG

Each is evaluated against nine dimensions including audio stimulus generation, real-time biosignal processing, ML/AI integration, extensibility, and cross-platform support. The dimensions are defined as follows:

- **Audio Stimulus Generation** is the capability to synthesise, parameterise, and deliver acoustic signals with temporal precision sufficient for event-related potential research (typically sub-millisecond jitter). Tools satisfying this dimension must support programmable waveform specification and hardware-synchronised onset triggers.
- **Visual Stimulus Support** is the ability to present time-locked visual stimuli alongside or independently of auditory paradigms, enabling multi-modal experimental designs.

- **Real-Time Biosignal Processing** is the continuous acquisition and online processing of physiological signals (EEG, EMG, ECG) with latencies low enough to support neurofeedback or adaptive paradigm control, typically below 100 ms end-to-end.
- **Neurofeedback Support** is the provision of closed-loop feedback to participants based on decoded biosignal features, including threshold detection, spectral band power, or event-related classification outputs.
- **Adaptive Paradigm Control** is the capacity to modify experimental parameters (stimulus intensity, frequency, timing, or trial sequence) dynamically in response to incoming physiological or behavioral data, enabling participant-specific protocol adaptation.
- **ML/AI Integration** is native support for machine learning or deep learning inference within the tool's processing pipeline, including the ability to load pre-trained models, execute classification or regression in real time, and expose prediction outputs to other system components.
- **Multi-Modal Signal Support** is the simultaneous acquisition and processing of multiple biosignal modalities (e.g., EEG combined with EMG, EOG, GSR, or cardiovascular signals) within a single processing environment.
- **Open Source** is the availability of the complete source code under an OSI-approved licence, enabling community auditing, modification, and redistribution without commercial restrictions.
- **Cross-Platform** is verified operation on at least two major operating systems (Windows, macOS, Linux), reducing barriers to adoption across heterogeneous laboratory environments.

Each tool is rated as:

- "Yes" – full support with documented evidence
- "Partial" – limited or indirect support requiring workarounds or external plugins
- "No" – absent functionality

This three-level scale was chosen to balance granularity with the reliability achievable from published documentation and source-code inspection alone, without conducting independent benchmarks.

Stimulus Delivery Platforms

- **PsychoPy** is a free, open-source experiment builder written in Python [1], offering both a graphical Builder and code-based Coder interface. It achieves sub-millisecond timing precision [7], supports hardware triggers for EEG synchronisation, and enables online deployment via Pavlovia. However, it includes no capacity for real-time biosignal processing or ML-based analysis.

- **OpenSesame** is an open-source graphical experiment builder [2] with a plugin-based architecture, drag-and-drop GUI, and Python scripting. An extension by Khodadadi et al. [8] achieved audio jitter of 0.42 ms and latency of 0.03 ms on Linux. Like PsychoPy, it is limited to stimulus presentation and response capture with no biosignal processing or ML capabilities.

Both platforms are mature and well-validated for Stage 1 but treat physiological response analysis as an entirely external concern.

Biosignal Feedback Tools

- **BrainBay** is an open-source, Windows-based neurofeedback application [3] implementing a visual programming language for constructing signal processing chains. It supports EEG, ECG, EMG, EOG, BVP, GSR, and skin temperature, with hardware support including ModularEEG, MonolithEEG, Optima, and OpenBCI boards. Neurofeedback operates via threshold detection. The critical limitation is the absence of structured stimulus generation BrainBay cannot deliver parameterised experimental audio stimuli, is restricted to Windows, and incorporates no machine learning.

Adaptive Paradigm Frameworks

- **BART (Brain Analysis in Real-Time)** is an open-source software package [4] for adaptive fMRI paradigms, with a modular architecture separating data input, real-time processing, stimulation, and device handling. Its core capability is physiologically-triggered stimulation: stimuli adapt based on incoming fMRI signals, representing conceptually the closest approach to a unified closed-loop platform. However, BART is exclusively coupled to fMRI. It cannot serve EEG-based or portable setups, and includes no machine learning component.

AI Foundation Models for EEG

- **ZUNA** is a 380M-parameter EEG foundation model [5], a masked diffusion autoencoder trained on 208 datasets (approximately 2M channel-hours). Its capabilities are channel infilling (reconstructing corrupted channels) and super-resolution (interpolating high-density configurations from sparse inputs), maintaining fidelity even at 90% dropout. ZUNA could improve EEG quality from consumer-grade equipment but does not classify brain states or interact with any stimulation system.

- **NeuroLM** is a 1.7B-parameter multi-task EEG foundation model [6] that treats EEG as a foreign language, using a text-aligned neural tokeniser and LLM architecture with multi-channel autoregression. Pre-trained on 25,000 hours of EEG data, it demonstrates substantial improvements over task-specific baselines across motor imagery, emotion recognition, and cognitive load classification. Like ZUNA, it has no mechanism for interfacing with stimulus delivery infrastructure.

AI foundation models represent the most rapidly advancing area reviewed, but their architectural independence from stimulation platforms means their transformative potential remains unrealised.

Comparative Analysis

- **Feature Comparison:** Table 1 presents a comparison across nine evaluation dimensions. The pattern is consistent: no single tool covers more than three dimensions, and the two most critical for a complete pipeline **audio stimulus generation** and **ML/AI integration** are never present together.

Table 1. Functional comparison of reviewed tools and models

Feature	PsychoPy	OpenSesame	BrainBay	BART	ZUNA	NeuroLM
Audio Stimulus Generation	**Yes**	**Yes**	No	Partial	No	No
Visual Stimulus Support	**Yes**	**Yes**	No	**Yes**	No	No
Real-Time Biosignal Processing	No	No	**Yes**	**Yes**	No	No
Neurofeedback Support	No	No	**Yes**	Partial	No	No
Adaptive Paradigm Control	Partial	No	No	**Yes**	No	No
ML/AI Integration	No	No	No	No	**Yes**	**Yes**
Multi-Modal Signal Support	No	No	**Yes**	No	No	No

Open Source	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Cross-Platform	**Yes**	**Yes**	No	**Yes**	**Yes**	**Yes**

Table 1 summarizes the evaluation results across the nine dimensions defined in the Methodology section.

PsychoPy and **OpenSesame** cover Stage 1 exclusively. **BrainBay** and **BART** cover Stage 2. **ZUNA** and **NeuroLM** cover Stage 3. No tool spans all three stages, and the interface between stimulus delivery and intelligent response analysis is entirely unoccupied.

Results of Comparative Analysis

The comparative analysis makes explicit that the field's tools are individually capable but collectively fail to constitute an integrated platform.

No existing platform integrates programmable audio signal generation with automated, machine learning-driven reaction analysis within a single unified environment.

This disconnection reflects fundamental architectural incompatibilities between precision stimulus delivery, real-time biosignal monitoring, and deep learning-based classification. Consequences include reduced reproducibility, infeasibility of closed-loop paradigms outside fMRI, high technical barriers, and missed translational potential for clinical neurofeedback.

Proposed Unified Platform

The proposed Solution is a unified platform integrating audio signal generation, biosignal acquisition, and ML-driven analysis. The platform comprises four modules:

1. A **Stimulus Engine** for programmable audio delivery with sub-millisecond precision and parameterised protocols
2. An **Acquisition Layer** interfacing with consumer-grade and research-grade EEG hardware with integration points for ZUNA-style enhancement
3. An **Analysis Engine** supporting foundation models such as NeuroLM for automated brain response classification
4. A **Feedback Loop** consuming classification outputs to modulate stimulus parameters in real time. A plugin-based architecture inspired by BART would allow independent module replacement, with standardised data formats and open-source licensing.

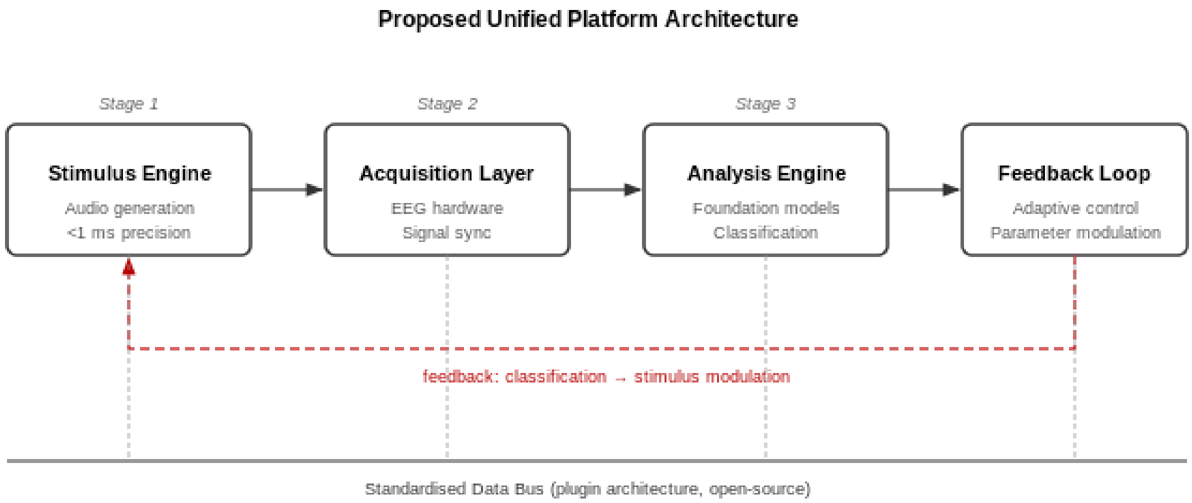

Figure 1. Proposed unified platform architecture with four modules and closed-loop feedback path

Discussion and Limitations

The fragmentation extends beyond audio stimulation: AI advances in brain signal analysis have not been matched by platforms enabling their use within experiments. Clinical applications of real-time ML-driven stimulation tinnitus neurofeedback, adaptive cochlear implants, audio-based BCIs remain unrealised without integrated infrastructure. Limitations include the review's focus on open-source tools and specificity to audio stimulation. A unified open-source platform would make pipelines explicit and shareable, supporting reproducibility.

Conclusion and Future Work

This review demonstrates that PsychoPy, OpenSesame, BrainBay, BART, ZUNA, and NeuroLM are architecturally isolated, each addressing a distinct pipeline portion. No existing platform integrates audio signal generation with ML-driven reaction analysis. Future work will proceed through requirements specification, prototype implementation, validation using canonical paradigms (oddball, ASSR, binaural beat), and evaluation in an applied BCI context. The platform will be released as open-source software.

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