International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Sonata AI: Electroencephalogram (EEG)-Based AI Music Therapy and Seizure Prevention for Neurodivergent Individuals with Epilepsy

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Abstract

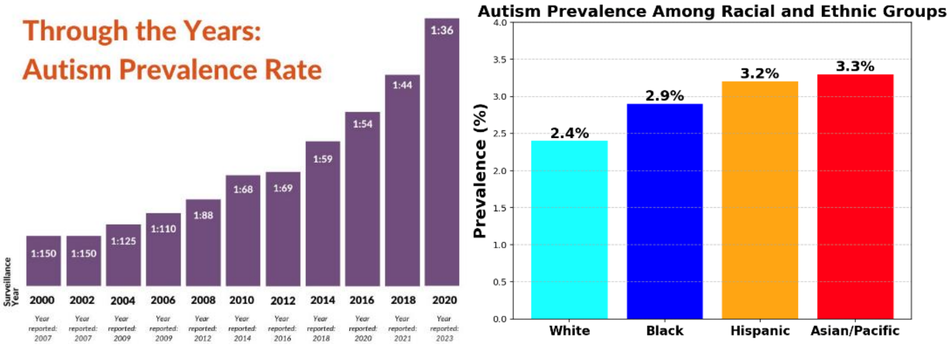
Autism Spectrum Disorder (ASD) affects 1 in 36 children and over 5 million adults in the US. This project is to deliver personalized music therapy to neurodivergent individuals using Artificial Intelligence (AI) to improve sensory integration and relaxation. We conducted a study to examine the impact of music on brainwaves in both neurodivergent and neurotypical individuals. We chose the music instrument e.g., piano, violin and cello for each participant. Our study included 3 neurodivergent males and 10 neurotypical individuals, male and female. We used the Neurosity Crown to stream real-time EEG data from 8 electrodes, collecting brainwave power across delta, theta, alpha, beta, and gamma bands, with and without music, and with eyes open or closed. We implemented JavaScript and Python scripts to do data collection, processing, and analysis. Results showed that neurodivergent individuals may exhibit much higher brain activity across all regions, unlike neurotypical individuals, who displayed varied activity levels. In addition, our Interquartile Range (IQR) statistical results proved the need for customized music therapy since different neurodivergent individuals respond uniquely to different instruments: the violin was optimal for one neurodivergent participant, while the piano fits the other two. We trained a neural network (NN) using power features from the 8 electrodes collected during quiet time, labeled with the optimal instrument, to predict the best instrument for everyone. The NN achieved 98% prediction accuracy, demonstrating AI's potential to personalize music therapy for improved sensory integration and relaxation in neurodivergent individuals without lengthy testing sessions required.

Keywords: Music therapy, Neural Network, AI, Neurodivergent, Autism

1. INTRODUCTION

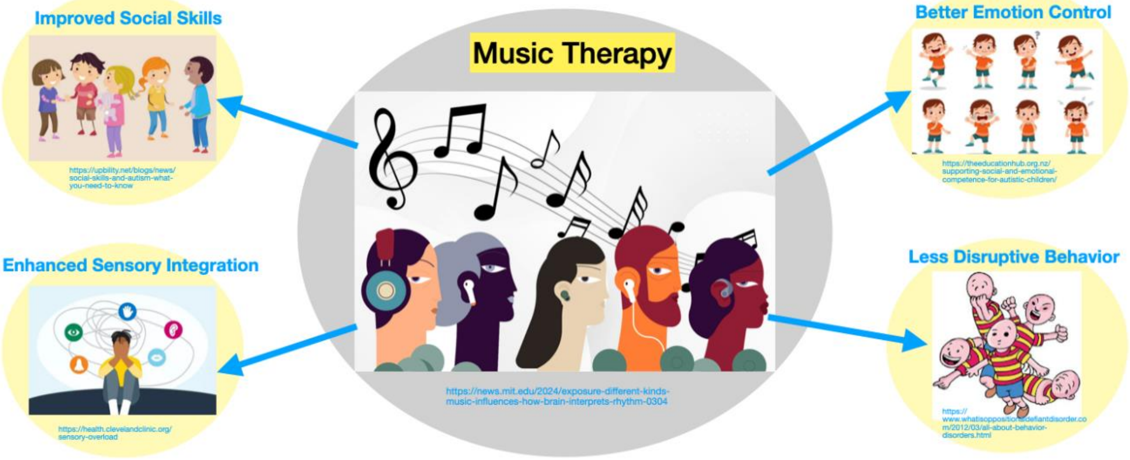
Autism Spectrum Disorder (ASD) is a growing public health concern, with prevalence rates rising significantly over the past two decades. As shown in Figure 1(a), in 2000, the diagnosis rate was 1 in 150 children, but by 2020, it had increased to 1 in 36, reflecting greater awareness, improved diagnostic criteria, and potential environmental or genetic factors[1]. Today, over 5 million adults in the U.S. live with ASD, further highlighting the need for effective support systems and interventions.

The prevalence of autism also varies across racial and ethnic groups. Figure 1(b) indicates that Asian/Pacific (3.3%) and Hispanic (3.2%) populations have the highest autism prevalence, followed by Black (2.9%) and White (2.4%) populations[2]. These differences may be influenced by disparities in healthcare access, cultural perceptions of neurodiversity, and diagnostic practices.



(a) (b)

Figure 1 (a) Autism Prevalence Rate through the years (b) Autism prevalence among racial and ethnic groups

With ASD affecting individuals across diverse backgrounds, therapeutic approaches must be inclusive and effective in addressing core challenges such as social interaction difficulties, sensory processing issues, emotional regulation struggles, and behavioral challenges. As shown in Figure 2, music therapy has emerged as a promising intervention, leveraging structured musical activities to enhance social skills, sensory integration, emotional control, and reduce disruptive behaviors[3-14].

https://upbility.net/blogs/news/social-skills-and-autism-what-you-need-to-know

https://theeducationhub.org.nz/supporting-social-and-emotional-competence-for-autistic-children/

https://news.mit.edu/2024/exposure-different-kinds-music-influences-how-brain-interprets-rhythm-0304

https://health.clevelandclinic.org/sensory-overload

https://www.whatisoppositionaldefiantdisorder.com/2012/03/all-about-behavior-disorders.html

Figure 2 Music therapy is a promising intervention to improve autistic symptoms

This paper explores the potential of personalized music therapy as a targeted intervention for neurodivergent individuals by addressing their unique sensory profiles. The goal is to develop an AI model capable of predicting the most effective music intervention based on an individual's real-time brain activity. By analyzing brain status, the model aims to recommend specific instruments and music types that enhance sensory integration, promote relaxation, and reduce anxiety. This research examines the feasibility of leveraging AI-driven insights to create adaptive, individualized music therapy, ultimately improving therapeutic outcomes for individuals with autism. In Section 2, we

This paper is structured as follows: **Section 2** outlines the design of the experiment, detailing the framework used to explore the relationship between brain activity and music intervention. **Section 3** describes the equipment and tools utilized, including EEG devices and software for data processing. **Section 4** explains the EEG data collection process and the methodology for analyzing brain activity patterns. **Section 5** presents the methods and results used to identify the optimal instrument for neurodivergent individuals based on their neural responses. **Section 6** focuses on the development of a neural network model designed to predict the most effective instrument for new individuals based on their brain activity. Finally, the paper concludes with a summary of findings and potential directions for future research

2. DESIGN OF THE EXPERIMENT

This study investigates the effects of different music interventions on neurodivergent and neurotypical individuals by analyzing brainwave activity. The goal is to establish measurable differences in neural responses to various instrument types, music genres, and listening conditions, providing the foundation for an AI-based predictive model for personalized music therapy.

2.1 Participants

The experiment includes two groups: three neurodivergent individuals (ages 10–15, all male) and ten neurotypical individuals (ages 15–82, male and female). This diverse participant pool allows for comparative analysis of neural responses across different populations. The inclusion of both neurodivergent and neurotypical individuals helps in distinguishing unique patterns in sensory processing and emotional regulation in response to music.

2.2 Variables

The study manipulates three independent variables: instrument type, music genre, and listening conditions. Participants listen to music played on the piano, violin, and cello, covering both classical and pop genres. The listening conditions include two states: one where participants listen to music with their eyes open and another serving as a baseline measurement with eyes closed and no music playing.

The dependent variables include brainwave activity recorded in real time EEG and Power Spectral Density (PSD), which quantifies neural responses to different music interventions. These metrics allow for objective assessment of sensory integration, relaxation, and emotional regulation in response to music.

2.3 Procedures

Each participant undergoes a structured sequence of sessions designed to assess their brain's response to various musical stimuli. The experiment begins with a baseline measurement, during which brainwave activity is recorded for five minutes while the participant sits with their eyes closed and no music playing. This serves as a reference point for comparison with the subsequent music listening sessions.

Following the baseline recording, participants engage in structured listening sessions with music played on different instruments. In the classical music sessions, participants listen to the piano, violin, and cello separately, with each session lasting five minutes. Their brain activity is monitored in real time to evaluate the differences in neural responses to each instrument. In the pop music sessions, participants select a song of their choice and listen for five minutes while their brain activity is recorded, allowing for an analysis of personalized music preferences on neural responses.

Each session lasts between 30 to 45 minutes and is repeated across multiple days and weeks to ensure reliability and account for variations in neural responses. The repetition of sessions strengthens the accuracy of the data, providing a robust foundation for training an AI model to predict the most effective music interventions for neurodivergent individuals.

3. EEG DATA ACQUISITION, PROCESSING, AND ANALYSIS TOOLS

This section outlines the equipment used for brainwave recording, the data processing pipeline, and the scientific basis for EEG analysis in relation to music intervention.

3.1 EEG Data Acquisition

The study utilizes the Neurosity Crown EEG headset[13] as shown in Figure 3 to record real-time brain activity, capturing various frequency bands and computing Power Spectral Density (PSD) values. EEG signals provide insights into neural responses to music interventions, helping to analyze sensory integration, relaxation, and cognitive engagement.

Figure 3 Neurosity Crown[13]

The Neurosity Crown is equipped with eight electrodes, placed according to the 10-20 international EEG system: F5, F6, C3, C4, CP3, CP4, PO3, and PO4. As demoed in Figure 4, each electrode captures neural activity from distinct brain regions[14].

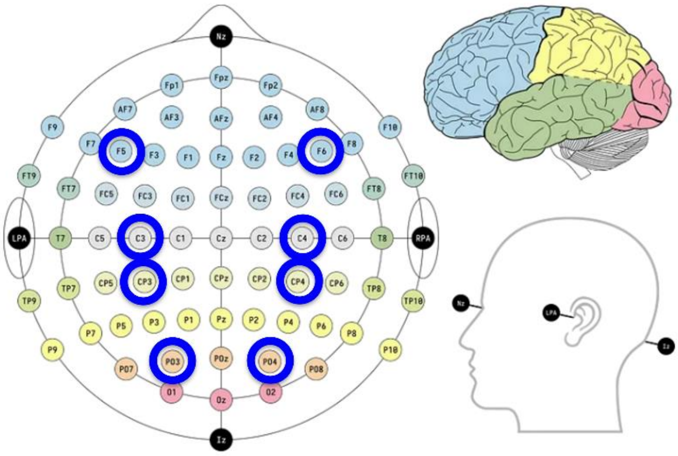


Figure 4 Neurosity 8 Electrodes (in blue circles) distribution: LPA to RPA is ear to ear with Cz being the center point of the head[14].

- F5 and F6 (Frontal Lobe): Associated with executive function, decision-making, and emotional regulation. Changes in activity in this region can indicate cognitive engagement, relaxation, or stress in response to music.
- C3 and C4 (Central Motor Cortex): Linked to motor coordination and sensorimotor processing, which may reflect rhythmic entrainment and involuntary movement responses to music.
- CP3 and CP4 (Parietal Cortex): Involved in sensory integration and spatial processing, these electrodes help assess how different musical elements influence sensory perception and body awareness.
- PO3 and PO4 (Occipital Cortex): Responsible for visual processing and mental imagery. Activity in this region may indicate how music stimulates visualization, emotional association, or memory recall.

3.2 EEG Data Storage

The Neurosity Crown SDK[15-16] provides a real-time interface for monitoring and analyzing brainwave activity. The attached snapshot showcases key EEG signal recordings and their corresponding Power Spectral Density (PSD) analysis, allowing for the assessment of how different musical interventions influence brain activity. The top section of the snapshot displays real-time EEG waveforms recorded from the eight electrodes: CP3, C3, F5, PO3, PO4, F6, C4, and CP4. Each line represents the signal strength and fluctuations of electrical activity detected at these locations. Changes in amplitude and pattern indicate variations in brain state, such as relaxation, focus, or stress, in response to different musical stimuli. Below the EEG waveform visualization, the Absolute Power by Band graph presents the relative strength of different frequency bands, including Delta (0.1–4 Hz), Theta (4–7.5 Hz), Alpha (7.5–12 Hz), Beta (12.5–30 Hz), and Gamma (>30 Hz). The power distribution across these bands provides insights into the participant's cognitive and emotional state during music listening. For example, an increase in Alpha waves suggests relaxation, while a rise in Beta waves indicates heightened focus and cognitive engagement. The PSD Symmetry graph on the right evaluates hemispheric balance by comparing the PSD values of left and right electrode pairs: C3 vs. C4, CP3 vs. CP4, F5 vs. F6, and PO3 vs. PO4. This metric is critical for understanding the lateralization of brain activity in response to different musical stimuli. Higher symmetry between left and right hemispheres suggests balanced neural engagement, while asymmetry may indicate a dominance of specific cognitive functions, such as emotional processing in the right hemisphere or analytical thinking in the left hemisphere.

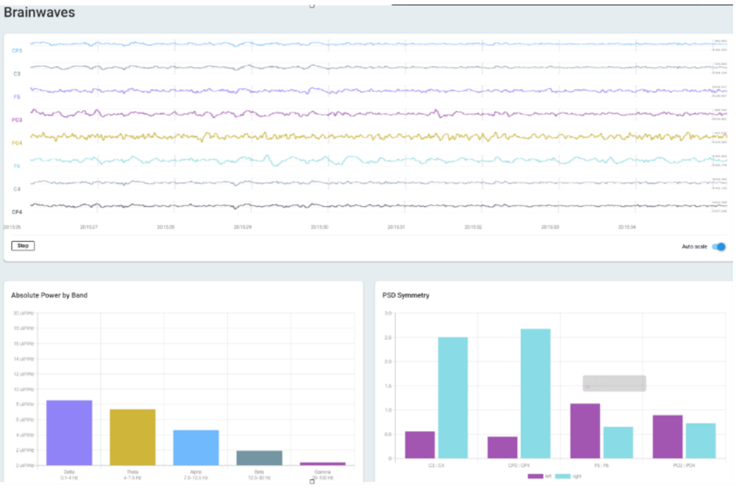


Figure 5 The Neurosity Crown SDK provides a real-time interface for monitoring and analyzing brainwave activity

To ensure structured and efficient data collection, the Neurosity Software Development Kit (SDK) is used to interface with the EEG headset. A custom Java program is developed to record real-time EEG and PSD data and store it in CSV format for further analysis.

For data analysis, Python is utilized, incorporating key scientific libraries:

- scikit-learn (sklearn): Used for machine learning applications, including classification and prediction modeling.
- NumPy: Employed for numerical operations and data manipulation.
- MNE (Magnetoencephalography and Electroencephalography Analysis Library): Used for EEG signal processing, feature extraction, and statistical evaluation of brainwave activity.

These tools facilitate the transformation of raw EEG signals into meaningful insights, supporting the development of an AI model capable of predicting the most effective music interventions for neurodivergent individuals.

3.3 EEG Data Processing Flow

The analysis of EEG data follows a structured pipeline to ensure accuracy, minimize artifacts, and enhance signal quality for meaningful interpretation. The preprocessing steps include denoising, bandpass filtering, and normalization to extract reliable neural activity patterns from the raw EEG recordings. Figure 6 is the EEG data processing.

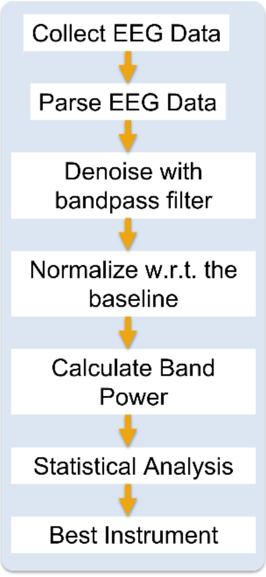


Figure 6 EEG data processing flow

Brainwave signals are first recorded from the Neurosity Crown headset in real time while participants listen to music. These signals, collected from eight electrodes (F5, F6, C3, C4, CP3, CP4, PO3, and PO4), provide insight into neural responses to different musical interventions. The raw EEG data is then parsed and formatted, ensuring correct labeling and structuring before further processing.

To remove unwanted noise, a bandpass filter between 0.5 Hz and 50 Hz is applied. EEG signals are often contaminated with low-frequency drifts from movement artifacts and high-frequency interference from electrical sources and muscle activity. The denoise_psd function implements noise removal using the MNE Python library. This function reshapes the EEG Power Spectral Density (PSD) data, applies the Finite Impulse Response (FIR) bandpass filter, and removes all frequency components outside the 0.5–50 Hz range. The lower cutoff eliminates slow drifts from electrode shifts or physiological artifacts, while the upper cutoff removes muscle and environmental noise. After filtering, the EEG data is reshaped back to its original format, and any negative values caused by processing artifacts are clipped to zero. This ensures that the cleaned EEG signals reflect only meaningful neural activity.

Following denoising, the EEG signals are normalized relative to a baseline condition, where the participant had their eyes closed and was not listening to music. The normalize_psd function standardizes the EEG power spectral data by computing the ratio of EEG activity during music listening to the average pre-music baseline values. The logarithmic transformation log1p is applied to control extreme variations and enhance interpretability, with a small constant added to prevent division by zero. This normalization step ensures that changes in brainwave power are attributed to the music intervention rather than individual differences in baseline neural activity.

Once the EEG data is filtered and normalized, the power of each frequency band (Delta, Theta, Alpha, Beta, Gamma) is calculated. These power measurements provide quantitative insights into neural engagement, sensory integration, relaxation, and cognitive processing. Statistical analysis is then performed to compare the effects of different musical instruments on EEG responses across neurotypical and neurodivergent participants.

Finally, based on the EEG power analysis and statistical results, the most effective musical intervention is identified for each participant. The best instrument is determined by evaluating which music type produced the most favorable neural activity, such as enhanced relaxation, improved sensory integration, or heightened cognitive engagement.

This structured EEG processing pipeline ensures that only high-quality data is used for analysis, supporting the development of an AI model capable of predicting the optimal music intervention for neurodivergent individuals based on their real-time brain activity.

3.4 Brainwave Frequency and Interpretation

A fundamental aspect of analyzing EEG data is understanding the relationship between different brainwave frequencies and mental states. The table below summarizes the five primary brainwave bands, their frequency ranges, associated mental states, and interpretations:

- Delta waves (0.5–4 Hz): Typically associated with deep sleep, unconscious states, and healing. Increased delta activity during wakefulness may indicate brain dysfunction or extreme fatigue.
- Theta waves (4–8 Hz): Linked to light sleep, deep relaxation, and creativity. While heightened theta activity can enhance creative thinking and meditation, excessive levels when awake may indicate fatigue or inattentiveness.
- Alpha waves (8–12 Hz): Represent a calm, relaxed, and reflective state. Increased alpha waves correlate with improved learning ability and stress reduction, but excessive alpha activity may lead to drowsiness or disengagement.
- Beta waves (12–30 Hz): Associated with focus, problem-solving, and active mental effort. Higher beta activity can improve cognitive performance, but excessive beta waves may indicate anxiety or stress.
- Gamma waves (30–100 Hz): Reflect heightened cognition, intense focus, and advanced problem-solving. Increased gamma activity is often linked to sharper insight and enhanced cognitive processing.

By integrating these EEG signal interpretations with music intervention data, this study aims to develop an AI model capable of predicting the most effective musical stimuli for neurodivergent individuals based on real-time brain activity.

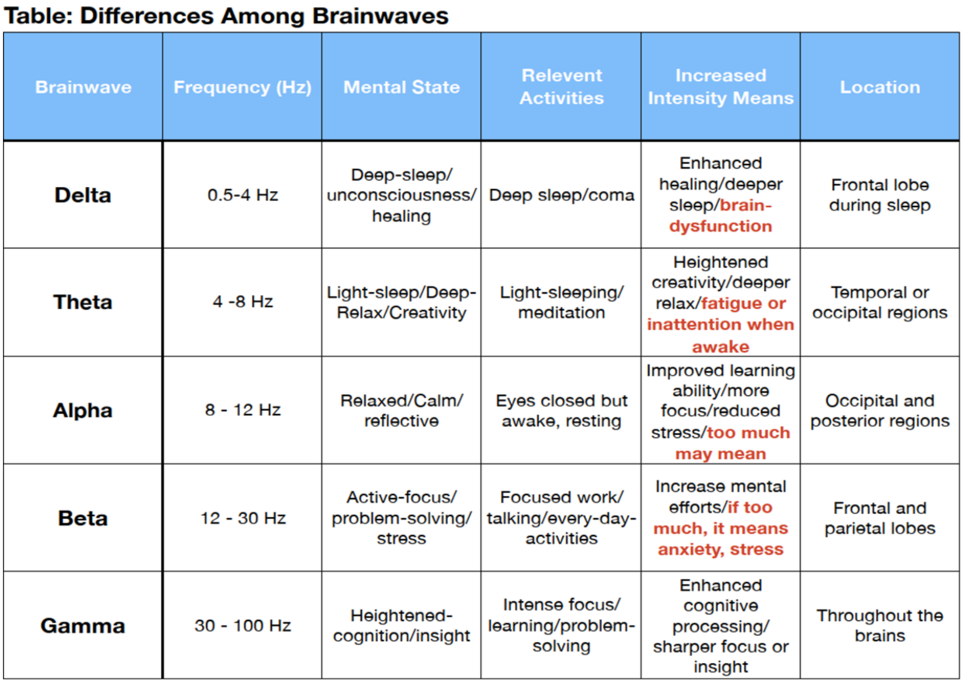


Table: Differences Among Brainwaves

Brainwave	Frequency (Hz)	Mental State	Relevent Activities	Increased Intensity Means	Location
Delta	0.5-4 Hz	Deep-sleep/ unconsciousness/ healing	Deep sleep/coma	Enhanced healing/deeper sleep/**brain-dysfunction**	Frontal lobe during sleep
Theta	4 -8 Hz	Light-sleep/Deep-Relax/Creativity	Light-sleeping/ meditation	Heightened creativity/deeper relax/**fatigue or inattention when awake**	Temporal or occipital regions
Alpha	8 - 12 Hz	Relaxed/Calm/ reflective	Eyes closed but awake, resting	Improved learning ability/more focus/reduced stress/**too much may mean**	Occipital and posterior regions
Beta	12 - 30 Hz	Active-focus/ problem-solving/ stress	Focused work/ talking/every-day-activities	Increase mental efforts/**if too much, it means anxiety, stress**	Frontal and parietal lobes
Gamma	30 - 100 Hz	Heightened-cognition/insight	Intense focus/ learning/problem-solving	Enhanced cognitive processing/ sharper focus or insight	Throughout the brains

4. RESULTS AND ANALYSIS

4.1 Brainpower Analysis: Neurodivergent vs. Neurotypical Responses

Figure 7 shows the brain power comparison among different individuals when listening to cello.

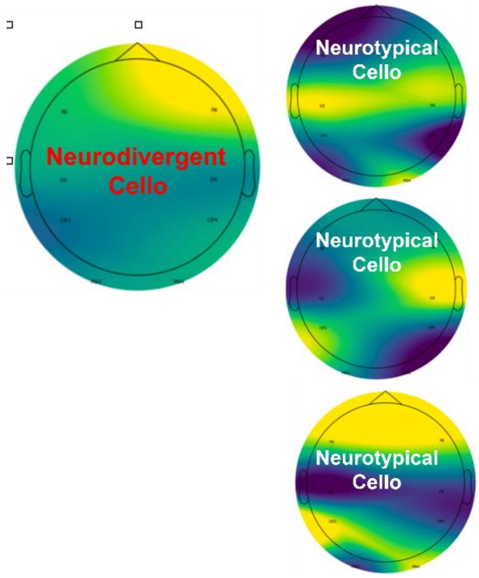


Figure 7 brain power comparison among neurodivergent and neurotypical individuals

The brainpower heatmaps illustrate EEG activity during music listening, comparing neurodivergent and neurotypical individuals. These topographic maps visualize differences in brainwave power distribution across the scalp, allowing for an analysis of how each group processes cello music.

For neurodivergent individuals, the heatmap shows stronger activation in the frontal and right parietal regions. This suggests a heightened engagement in emotional processing and sensory integration, indicating a more immersive response to music. The lower activation in occipital regions suggests that visual processing plays a less dominant role in their experience, with a stronger emphasis on auditory and sensory processing.

Neurotypical individuals exhibit a more balanced distribution of brain activity across both hemispheres. Unlike the neurodivergent response, the neurotypical brainpower maps show less pronounced frontal activation but increased activity in the occipital and parietal regions. This pattern suggests that neurotypical individuals may engage more in mental imagery and associative thinking while listening to music. The symmetrical activation across both hemispheres reflects a more distributed cognitive response, likely integrating auditory input with spatial and memory-related processing.

These findings suggest that neurodivergent individuals may process cello music differently, relying more on emotional and sensory processing rather than visualization or memory-related associations. Understanding these differences allows for the development of a data-driven approach to personalized music therapy, where music interventions are tailored based on real-time EEG activity. This research supports the creation of an AI model capable of predicting the most effective musical stimuli for neurodivergent individuals, optimizing music therapy for enhanced sensory and cognitive benefits.

4.2 Comparison of EEG Power Distribution Across Music Stimuli: Neurodivergent vs. Neurotypical Responses

Understanding the distribution of EEG power across different musical stimuli is essential for identifying the optimal instrument for neurodivergent individuals. To analyze these distributions, this study utilizes

Interquartile Range (IQR), a statistical measure that describes the spread of EEG power values within each frequency band.

The Interquartile Range (IQR) represents the middle 50% of a dataset, spanning from the first quartile (Q1, 25th percentile) to the third quartile (Q3, 75th percentile). The IQR (Q3 - Q1) provides insights into the variability of EEG responses, with a larger IQR indicating greater neural response variability and a smaller IQR suggesting more consistent neural activation across participants.

In the boxplots used for this analysis, each box represents the IQR, with the median (50th percentile) displayed as a line within the box. The whiskers extend to 1.5 times the IQR, capturing most of the data range, while outliers appear as individual dots beyond the whiskers, representing extreme EEG power values.

By examining IQR and EEG power distributions across different instruments (Cello, Violin, Piano, and Pop) and brainwave frequency bands (Delta, Theta, Alpha, Beta, and Gamma), this section aims to determine which musical intervention elicits the most favorable neural response for neurodivergent individuals. The following analysis explores EEG power variations between neurotypical (NT) and neurodivergent (ND) groups to assess how different music stimuli impact sensory integration, cognitive engagement, and emotional regulation.

Figure 8 provides a comparative analysis of EEG power distribution between neurodivergent (ND) and neurotypical (NT) individuals across different brainwave frequency bands. The X-axis represents EEG power categorized by group, music stimulus, and frequency band, while the Y-axis represents power spectral density (PSD), which quantifies the strength of neural oscillations.

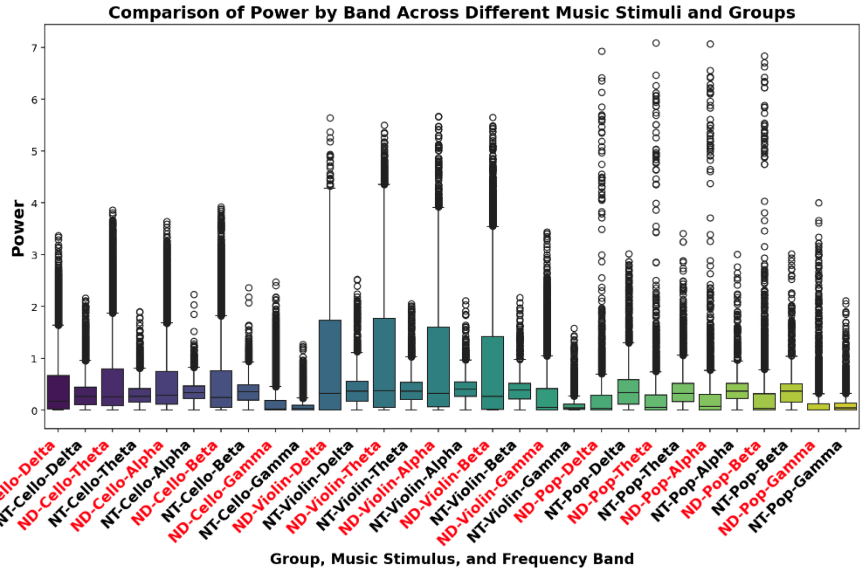


Figure 8 Comparison of power by band across different music stimuli and groups i.e., neurodivergent Vs. Neurotypical

The results highlight clear differences in EEG power distributions between ND and NT individuals. Across all music stimuli, ND individuals exhibit greater variability in Theta, Alpha, and Gamma power, as shown by wider interquartile ranges (IQRs) and a higher number of outliers. This suggests that ND individuals experience more variable neural responses across different conditions, particularly in brainwave frequencies associated with sensory processing and cognitive integration.

In contrast, NT individuals show more consistent EEG power distributions, with narrower IQRs and fewer outliers, indicating a more stable and predictable neural response to musical stimuli. The relative uniformity of their brainwave power suggests a more regulated neural processing pattern, whereas the increased variability in ND individuals reflects individual differences in sensory and cognitive responses. Additionally, ND individuals display higher instances of extreme power values, where the number of outliers is significantly greater compared to NT individuals. This suggests that some ND individuals may experience heightened neural activity or overstimulation in response to music, whereas NT individuals tend to exhibit a more balanced neural activation.

Overall, the analysis indicates that ND individuals exhibit greater variability and outliers in their EEG power distributions, while NT individuals demonstrate more stable and predictable neural responses. These differences highlight the importance of personalized music interventions for ND individuals, as their responses to auditory stimuli are less uniform and require tailored approaches based on real-time EEG patterns.

4.3 Identifying the Optimal Music Instrument for Neurodivergent Individuals

The individualized EEG power analysis across different music stimuli provides insight into how neurodivergent individuals respond to various instruments. Figure 9 shows the box plots for three neurodivergent participants (ND#1, ND#2, and ND#3) illustrate the distribution of EEG power across frequency bands when exposed to different musical interventions. The goal is to determine which instrument elicits optimal neural responses by balancing sensory integration (Theta, Alpha, Gamma) and relaxation (Alpha), while avoiding excessive activation that may indicate overstimulation.

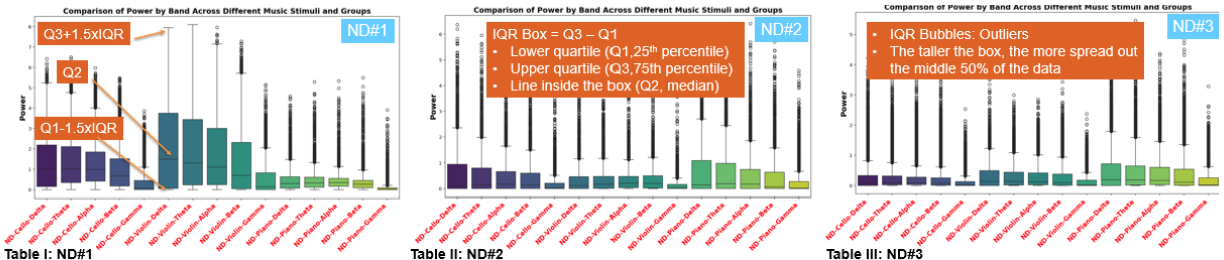


Table I: ND#1

Music	Sensory Integration (Theta/Alpha/Gamma)	Relaxation (Alpha)
Cello	Moderate	Moderate
Violin	**High**	**High**
Piano	Low	Low

Table II: ND#2

Music	Sensory Integration (Theta/Alpha/Gamma)	Relaxation (Alpha)
Cello	Moderate	Moderate
Violin	Low	Low
Piano	**High**	**High**

Table III: ND#3

Music	Sensory Integration (Theta/Alpha/Gamma)	Relaxation (Alpha)
Cello	Low	Low
Violin	Moderate	Moderate
Piano	**High**	**High**

Figure 9: Boxplots and sensory-integration/relaxation summaries for 3 neurodivergent individuals

For ND#1, Violin exhibits the highest neural activation, particularly in Theta and Gamma bands. This suggests that Violin enhances sensory integration for this individual, making it a strong candidate for intervention. However, the variability in Beta activity indicates that it could also introduce cognitive stimulation, which may or may not be beneficial depending on the context.

For ND#2 and ND#3, Piano shows the highest EEG power, particularly in Theta and Alpha bands. The consistent Alpha activation suggests that Piano effectively promotes relaxation, while the elevated Theta power supports sensory integration. Compared to Violin, the EEG responses to Piano appear more stable, with less variability and fewer extreme outliers, indicating a more predictable and controlled neural response.

The key takeaway from these findings is that the optimal instrument for neurodivergent individuals is highly individualized. ND#1 responds best to Violin, whereas ND#2 and ND#3 show stronger and more stable responses to Piano. This reinforces the importance of personalized music therapy, where EEG data can guide intervention choices based on real-time neural responses.

By leveraging these insights, an AI-driven model can be trained to predict the most effective music intervention for each individual based on their EEG power distribution. This approach ensures that neurodivergent individuals receive tailored music therapy that enhances sensory integration and relaxation while minimizing overstimulation.

5. AI MODEL FOR PREDICTING THE BEST INSTRUMENT FOR NEURODIVERGENT INDIVIDUALS

The goal of this section is to develop a neural network (NN) model that can predict the most effective musical instrument for neurodivergent individuals based on their baseline EEG data. This approach enables personalized music interventions without requiring repeated trials of different instruments, making music therapy more efficient and tailored to everyone's neural processing patterns. The AI model follows a structured pipeline as shown in Figure 10.

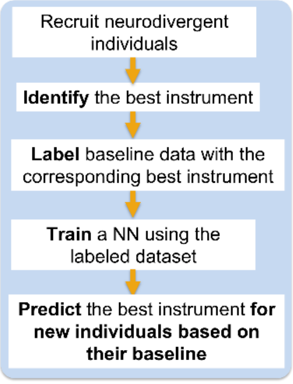


Figure 10. AI flow

First, neurodivergent individuals are recruited for data collection. Their EEG responses to different musical stimuli are recorded and analyzed to identify the best instrument for everyone using the flow addressed in Section 4, based on optimal Theta, Alpha, and Gamma power for sensory integration and Alpha power for relaxation

Once the best instrument is determined, the individual's baseline EEG data (recorded with eyes closed and no music) is labeled with the corresponding best instrument. This forms the labeled dataset, where each participant's natural resting-state brain activity is mapped to the instrument that elicited the most beneficial response during active listening.

The labeled dataset is then used to train a neural network (NN), enabling it to learn patterns in baseline EEG activity that correlate with specific musical preferences. The NN model is trained to recognize hidden relationships between resting-state brain activity and optimal music interventions, generalizing these patterns across participants. This data-driven, brain-based approach surpasses conventional methods by ensuring that recommendations are grounded in measurable neurophysiological patterns rather than subjective preferences or external assumptions.

Finally, the trained NN model is used to predict the best instrument **for new neurodivergent individuals** based solely on their baseline EEG data. By analyzing their resting-state brain activity, the AI model can suggest the most suitable musical intervention without requiring them to listen to multiple instruments, making the process faster and more accessible. Unlike traditional trial-and-error approaches in music therapy, which rely on subjective observation and behavioral assessments, our model leverages objective neural data to personalize interventions efficiently.

5.1 Neural Network Architecture

The neural network (NN) model is designed to predict the most suitable musical instrument for neurodivergent individuals based on their baseline EEG features. The architecture follows a standard multi-layer perceptron (MLP) structure, consisting of an input layer, hidden layers, and an output layer as shown in Figure 11.

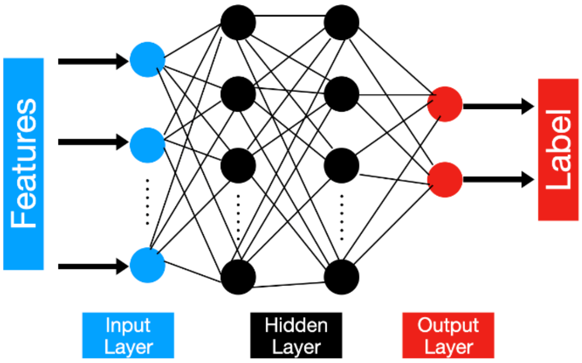


Figure 11 Neural Network Architecture

The neural network (NN) is designed as a multi-layer perceptron (MLP) to classify neurodivergent individuals' baseline EEG activity and predict the most suitable musical instrument. The architecture consists of an input layer, two hidden layers, and an output layer, trained using a supervised learning approach.

The input layer consists of eight neurons, each representing EEG power spectral features extracted from the electrodes C3, C4, CP3, CP4, F5, F6, PO3, and PO4 under the baseline (eyes closed, no music) condition. These features serve as the foundation for predicting the best instrument.

The hidden layers include two fully connected layers, each with 16 neurons, applying the ReLU (Rectified Linear Unit) activation function to introduce non-linearity and allow the network to capture complex relationships in EEG patterns. ReLU is a simple yet effective activation function that replaces negative values with zero while keeping positive values unchanged.

The output layer is designed to accommodate multiple possible instruments, with each neuron representing a different class. In this demonstration, we use two output neurons corresponding to Violin (class 1) and Piano (class 2). However, this design is scalable and can be expanded to include more musical instruments as additional data becomes available. The network applies softmax activation in the output layer, which converts the raw output values into probabilities that sum to one. This allows the model to assign a likelihood score to each instrument, making it suitable for multi-class classification.

The model is trained using Categorical Cross-Entropy, a loss function commonly used in multi-class classification problems. It measures how far the predicted probability distribution is from the actual label, encouraging the network to produce accurate classifications. To optimize the learning process, we use the Adam optimizer, a widely used algorithm that adjusts the learning rate dynamically for each parameter.

The training process is conducted in mini-batches of 16 samples at a time (batch size = 16) rather than feeding the entire dataset at once. This balances computational efficiency and stability in weight updates. The model is trained over 50 epochs, meaning the entire dataset is passed through the network 50 times to refine its predictions gradually.

This neural network architecture is designed to be scalable and adaptable, allowing for the future inclusion of additional musical instruments. Once trained, the NN model can **take EEG data from new individuals and predict their most suitable instrument without requiring direct exposure to multiple music**

stimuli. This AI-driven approach enhances efficiency in personalized music therapy by eliminating the need for exhaustive trials, ensuring that neurodivergent individuals receive interventions optimized for sensory integration and relaxation based on real-time neural patterns.

5.2 Data Preparation for Neural Network Training

A critical challenge in using baseline EEG data for predicting the best instrument is that an individual's brain activity varies across different days and moments due to factors such as mood, fatigue, attention levels, and external influences. This natural fluctuation introduces variability in EEG signals, making it essential for our AI model to be robust and adaptive in handling these changes.

To address this, our neural network is trained on multiple baseline recordings from the same individual over different sessions, ensuring that the model learns to recognize consistent neural patterns rather than momentary fluctuations. By incorporating data from different time points, the model becomes more generalizable, reducing the impact of temporary shifts in brain activity.

Additionally, instead of relying on raw EEG power alone, our approach focuses on relative features—such as the z-score normalized power spectral density (PSD) changes across electrodes and frequency bands—which are more stable over time. This ensures that the model identifies intrinsic neural signatures rather than being overly sensitive to short-term variations. By designing the model to accommodate the dynamic nature of baseline EEG, we ensure that predictions remain reliable and personalized, even as an individual's brain activity fluctuates over time.

Each sample is then labeled based on the best instrument identified for the individual. Labels are one-hot encoded for multi-class classification, allowing the neural network to recognize different instruments as separate categories. To prevent bias in training, the dataset is examined for class imbalances. If necessary, the minority class is up-sampled by duplicating existing samples to match the majority class, ensuring the model learns equally from all labels.

5.3 Neural Network Training and Prediction

Once the dataset is structured, it is split into 80% training and 20% testing to evaluate model performance. The neural network was trained and evaluated on a limited dataset, consisting of 528 training samples and 132 testing samples.

As shown in Figure 12, the loss curve reveals a steady decline for both training and testing datasets, eventually converging to a minimal value. The similarity between the two curves further confirms that the model effectively captures relationships between EEG power features and instrument labels without excessive overfitting.

Figure 12 Neural Network Training and Testing loss

The model achieved ~99% accuracy on the training set and ~98% accuracy on the testing set, demonstrating strong generalization. The accuracy curve shows that the model quickly learns patterns within the first few epochs and stabilizes, with training and testing accuracies remaining close, indicating no significant overfitting.

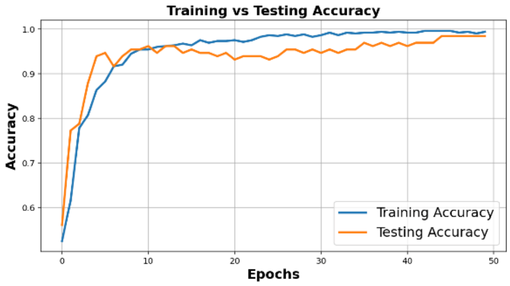


Figure 13 Neural Network Training and Testing Accuracy

A comparison of actual versus predicted class distributions shows that predictions align closely with the true labels. Only two misclassifications were observed, both cases where Class 1 (Violin) was mistakenly predicted as Class 2 (Piano). This minor error suggests that the model is highly reliable but may still require fine-tuning when applied to a broader population.

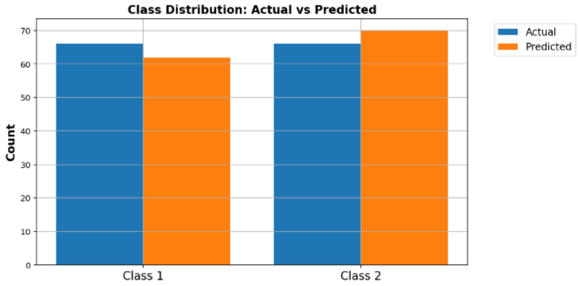


Figure 14 Neural Network Prediction on Class Distribution: Actual Vs. Predicted

By structuring EEG data efficiently and using a well-tuned neural network, this approach demonstrates the potential and the framework for an AI-driven personalized music therapy system, where future expansions with more training data can further refine its accuracy and applicability.

5.3 Discussion on Scalability and Impact of the NN Model

The AI-driven approach may enhance the accessibility and efficiency of music therapy, providing a scalable, non-invasive, and scientifically validated tool for tailoring interventions to neurodivergent individuals.

Once a well-trained neural network (NN) model is built, it can immediately scale to serve millions of neurodivergent individuals without the need for additional retraining or individualized trial sessions. Unlike traditional music therapy approaches, which require in-person evaluation and repeated exposure to different musical instruments, our AI system can instantly predict the best instrument for a new individual based on a simple baseline EEG recording.

This scalability is a major advantage, **as the model enables remote and automated assessments**, making personalized music interventions widely accessible. Patients can have their baseline EEG data collected in a single session, and the trained NN model will instantly classify the best instrument for their sensory integration and relaxation needs. This eliminates the time-consuming process of manually testing multiple instruments while ensuring recommendations are backed by objective neural data rather than subjective assessments.

Furthermore, the AI model continuously improves as more data is collected, allowing for ongoing refinement and adaptation to a wider range of neurodivergent individuals. This approach transforms music therapy from a manual, therapist-dependent process into a scalable, AI-powered system, capable of delivering highly personalized recommendations to a global population in need of effective interventions.

6. CONCLUSION

This study examined how music affects brainwave activity in neurodivergent and neurotypical individuals and developed an AI-driven system to personalize music therapy based on EEG data. Using the Neurosity Crown, EEG data was collected from participants under different conditions, both with and without music, with eyes open, to analyze how different instruments influence brain activity. Data processing was performed using custom Java and Python scripts, extracting Power Spectral Density (PSD) values to compare neural responses across different groups.

The findings revealed distinct differences in brain activity between neurodivergent and neurotypical individuals. Neurodivergent participants exhibited higher brain activity, while neurotypical individuals showed more varied and lower levels of activation. This suggests that neurodivergent individuals process auditory stimuli differently, emphasizing the need for personalized music therapy.

Through Interquartile Range (IQR) analysis, it was demonstrated that different instruments influence brainwave activity in unique ways. The study tested piano, cello, and violin, systematically analyzing their effects on theta, alpha, and gamma waves, which are associated with sensory integration and relaxation. The optimal instrument was identified for each neurodivergent participant, reinforcing the importance of individualized intervention strategies.

A multi-layer neural network (MLP) was developed to predict the best instrument based on baseline EEG activity. The model was trained using upsampled EEG features, achieving ~99% training accuracy and ~98% testing accuracy, with only minor misclassifications. The structured 5-timestamp window averaging method was critical in stabilizing EEG features, ensuring reliable classification despite limited data.

This research marks a significant step toward data-driven, AI-powered personal music therapy, enabling precise, scalable, and scientifically grounded treatment recommendations. While previous research has explored music's effects on the brain, no prior work has integrated machine learning and real-time EEG processing to create a system capable of predicting individualized music interventions. Future studies will focus on expanding the dataset, refining the neural network with additional instruments, and testing real-time adaptability. With continued development, this system has the potential to support millions of neurodivergent individuals, offering scientifically grounded, personalized music therapy recommendations that enhance cognitive and emotional well-being.

ACKOWNLEGEMENTS

The authors would like to thank the support of the students and parents at Friends of Children with Special Needs (FCSN) in participating in this study. The autors are grateful to the chemistry teacher, Ms. Katy Kuei, for her inspiring guidance.

REFERENCES

1. SARRC, https://autismcenter.org/autismprevalence
2. Autism speaks, https://www.autismspeaks.org/autism-statistics-asd#:~:text=In%20the%20U.S.%2C%20autism%20prevalence,Hispanic%20%E2%80%93%203.2%

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3. Erin Abel, Teresa Laking, The short-term effects of music therapy on anxiety in autistic children, UW-L Journal of Undergraduate research IX (2006), https://www.uwlax.edu/globalassets/offices-services/urc/jur-online/pdf/2006/azbell.laking.pdf
4. Blythe LaGasse, Ga Eul Yoo, Michelle Welde Hardy, Rhythm and music for promoting sensorimotor organization in autism: broader implications for outcomes, Frontiers in Integrative Neuroscience (2024), https://www.frontiersin.org/journals/integrative-neuroscience/articles/10.3389/fnint.2024.1403876/full
5. Slimen, I. B., Boubchir, L., & Seddik, H. (2020). Epileptic seizure prediction based on EEG spikes detection of ictal-preictal states. Journal of biomedical research, 34(3), 162–169, https://doi.org/10.7555/JBR.34.20190097
6. Trimble, M. R., Hesdorffer, D., Hećimović, H., & Osborne, N. (2024), Personalised music as a treatment for epilepsy. Epilepsy & behavior: E&B,156, 109829. https://doi.org/10.1016/j.yebeh.2024.109829
7. Santarone, M. E., Zambrano, S., Zanotta, N., Mani, E., Minghetti, S., Pozzi, M., Villa, L., Molteni, M., & Zucca, C. (2023). EEG Features in Autism Spectrum Disorder: A Retrospective Analysis in a Cohort of Preschool Children. Brain sciences, 13(2), 345.
8. Wong, S., Simmons, A., Rivera-Villicana, J., Barnett, S., Sivathamboo, S., Perucca, P., Ge, Z., Kwan, P., Kuhlmann, L., Vasa, R., Mouzakis, K., & O'Brien, T.J. (2023). EEG datasets for seizure detection and prediction- A review. Epilepsia open, 8(2), 252–267. https://doi.org/10.1002/epi4.12704
9. Sugden, R. J., Pham-Kim-Nghiem-Phu, V. L., Campbell, I., Leon, A & Diamandis, P. (2023). Remote collection of electrophysiological data with brain wearables: opportunities and challenges. Bioelectronic medicine, 9(1), 12. https://doi.org/10.1186/s42234-023-00114-5
10. Anon (2024). Learning music in times of lockdown (Radio column), https://capian.co/blog/learn-music-lockdown
11. Anon (2023). A Generative AI Primer. https://er.educause.edu/articles/2023/8/a-generative-ai-primer
12. Anon (2023). How to build a local digital music library.
13. Neurosity website, https://neurosity.co
14. Medium, Spatial Intuition for Neurosity Crown Electrode Placement, https://surajtirupati.medium.com/spatial-debrief-of-neurosity-crown-electrode-placement-af142aa949a9
15. Neurosity safety (2023). Neurosity CROWN Brain Gadget Instruction Manual. https://manuals.plus/neurosity/crown-brain-gadget-manual#declaration
16. Neurosity developers (2023). Neurosity SDK, https://docs.neurosity.co/docs/api/haptics